The importance of WEATHER IN SPACE and how data science will help us understand it

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NASA JPL, Dartmouth College

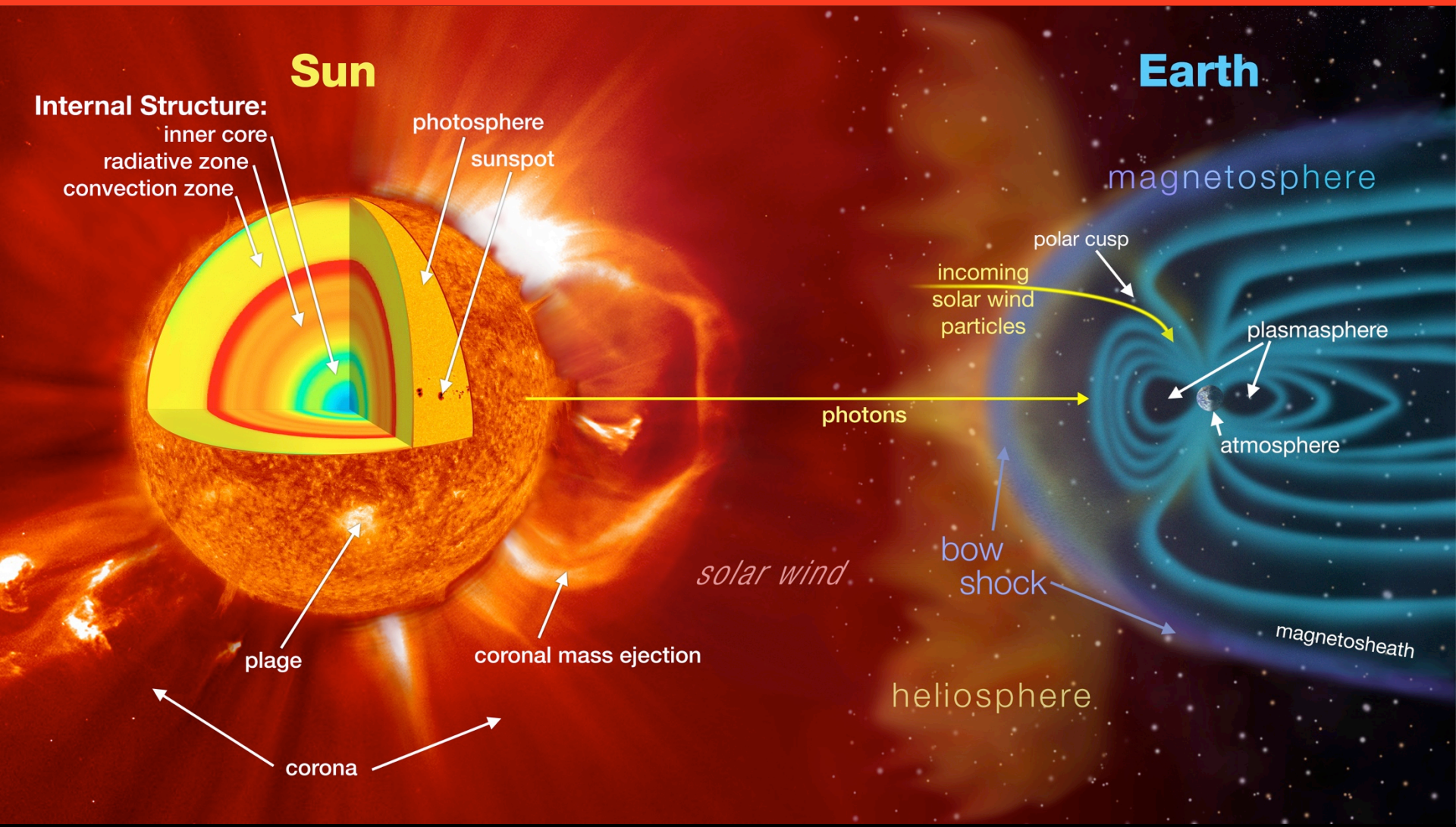
My story

Blueprint for today

What is space weather?

What is space weather?

Heliophysics & space weather - Data-driven space weather - Exciting future



What is space weather?

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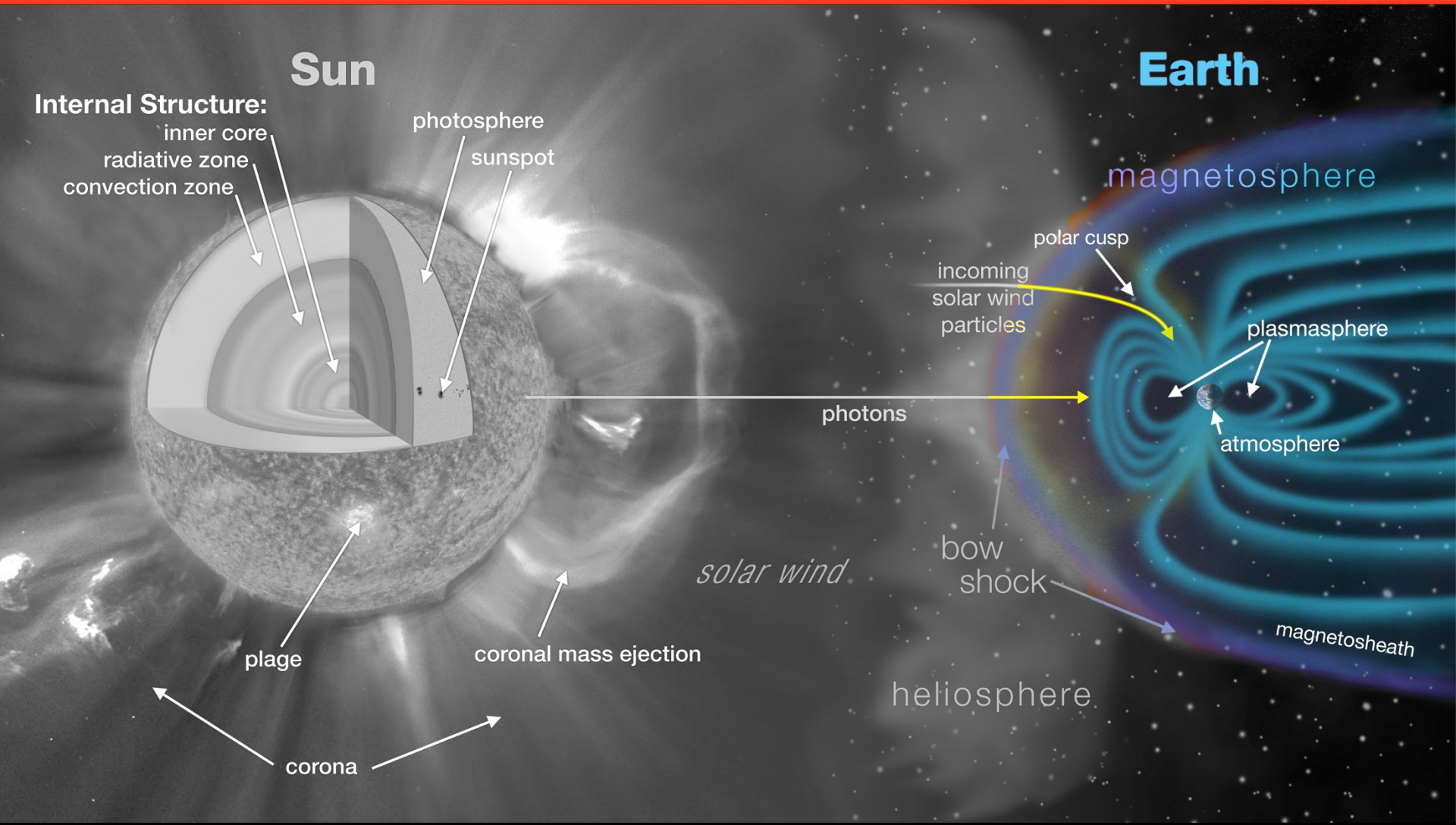
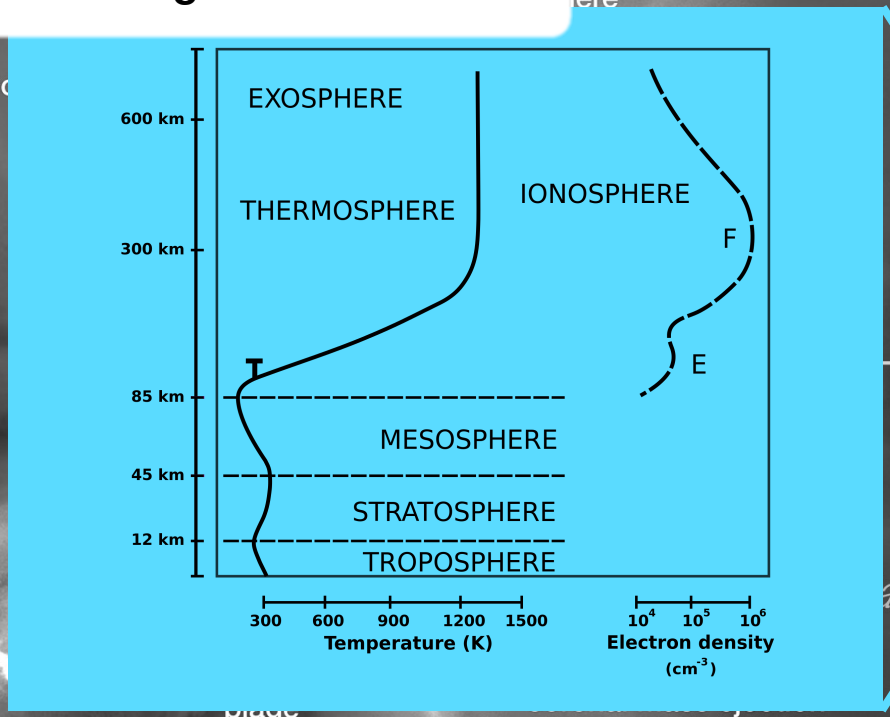
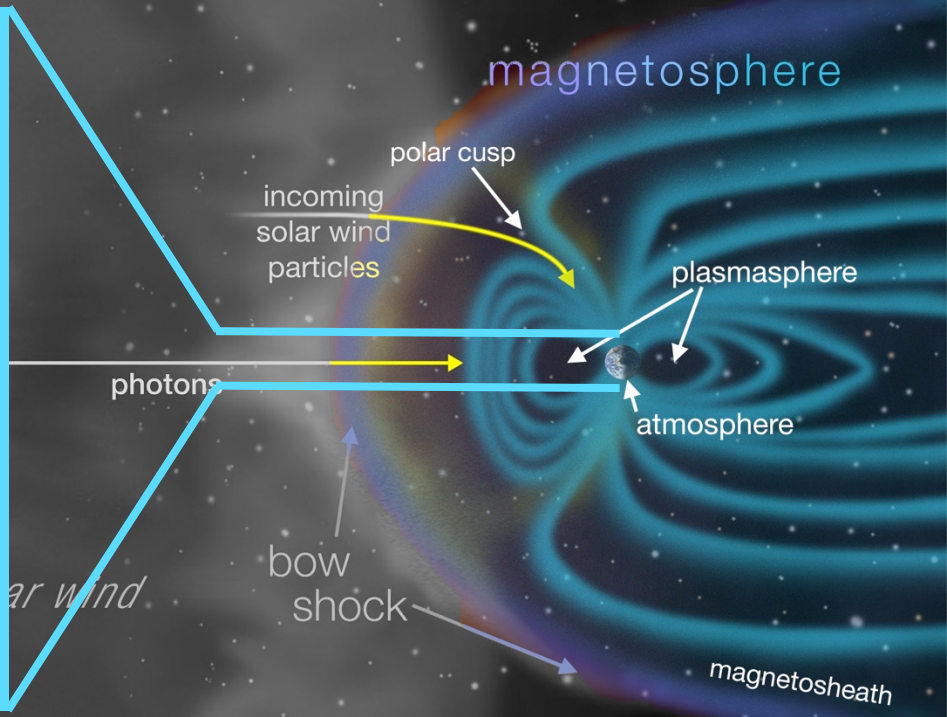


What is space weather?

Heliophysics & space weather - Data-driven space weather - Exciting future

Critical region: 100-1000 km

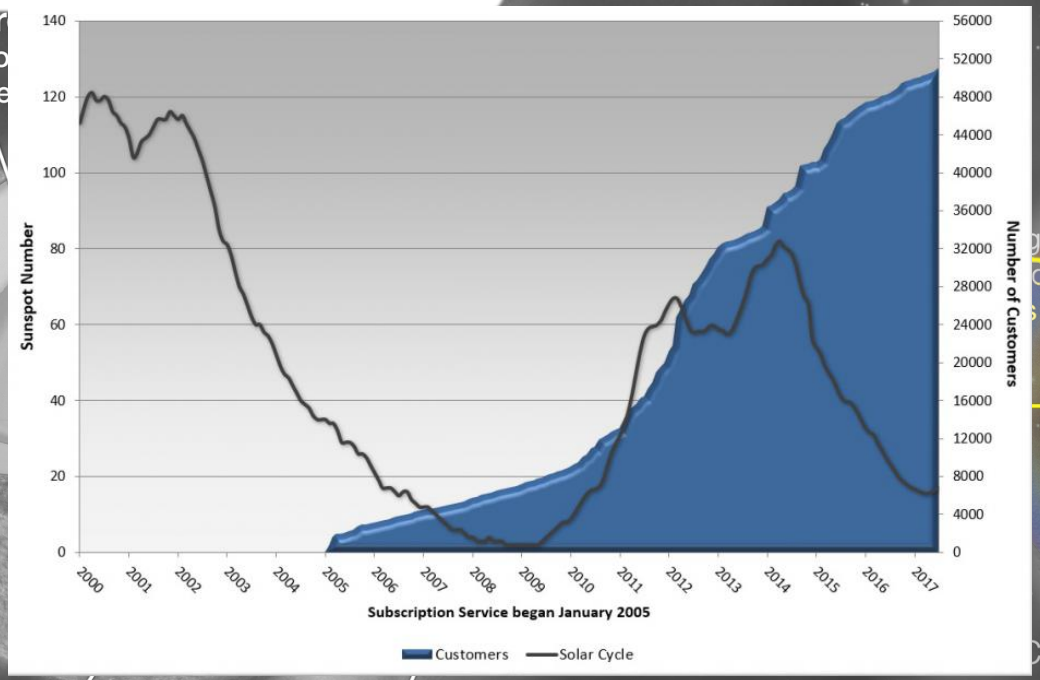




What is space weather?

Heliophysics & space weather - Data-driven space weather - Exciting future

Growth of space weather customers



Internal Structur
inner co
radiative zone
convection zone

Earth
magnetosphere
polar cusp
plasmasphere
atmosphere
magnetosheath

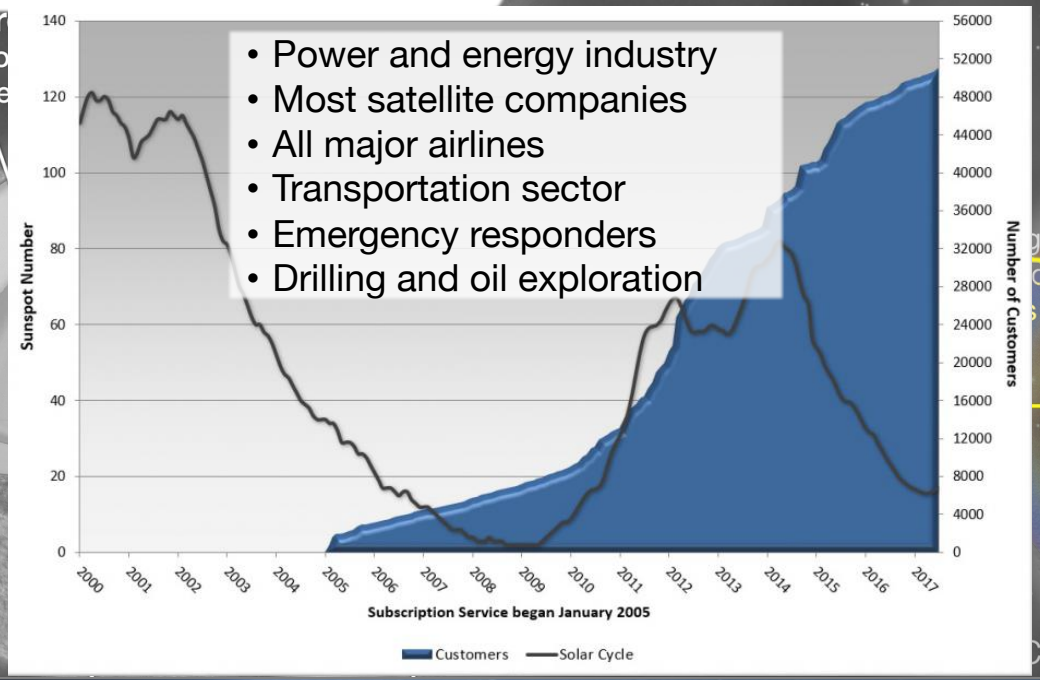
plage
coronal mass ejection
heliosphere
corona

What is space weather?

Heliophysics & space weather - Data-driven space weather - Exciting future

Growth of space weather customers

- Power and energy industry
- Most satellite companies
- All major airlines
- Transportation sector
- Emergency responders
- Drilling and oil exploration



Satellite companies	Banking	FEMA	Academia	FAA
Shipping	Automobile industry	Communication companies	Oil drilling	Electric utilities
State Departments of Transportation	Precision agriculture	Major airlines	United Launch Alliance	Surveying groups

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radiative zone
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Earth
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What is space weather?

CPAESS

NASA

- Data-driven space weather - Exciting future

NATIONAL SPACE WEATHER STRATEGY

PRODUCT OF THE

National Science and Technology Council

October 2015

NAL SPACE WEATHER ACTION PLAN

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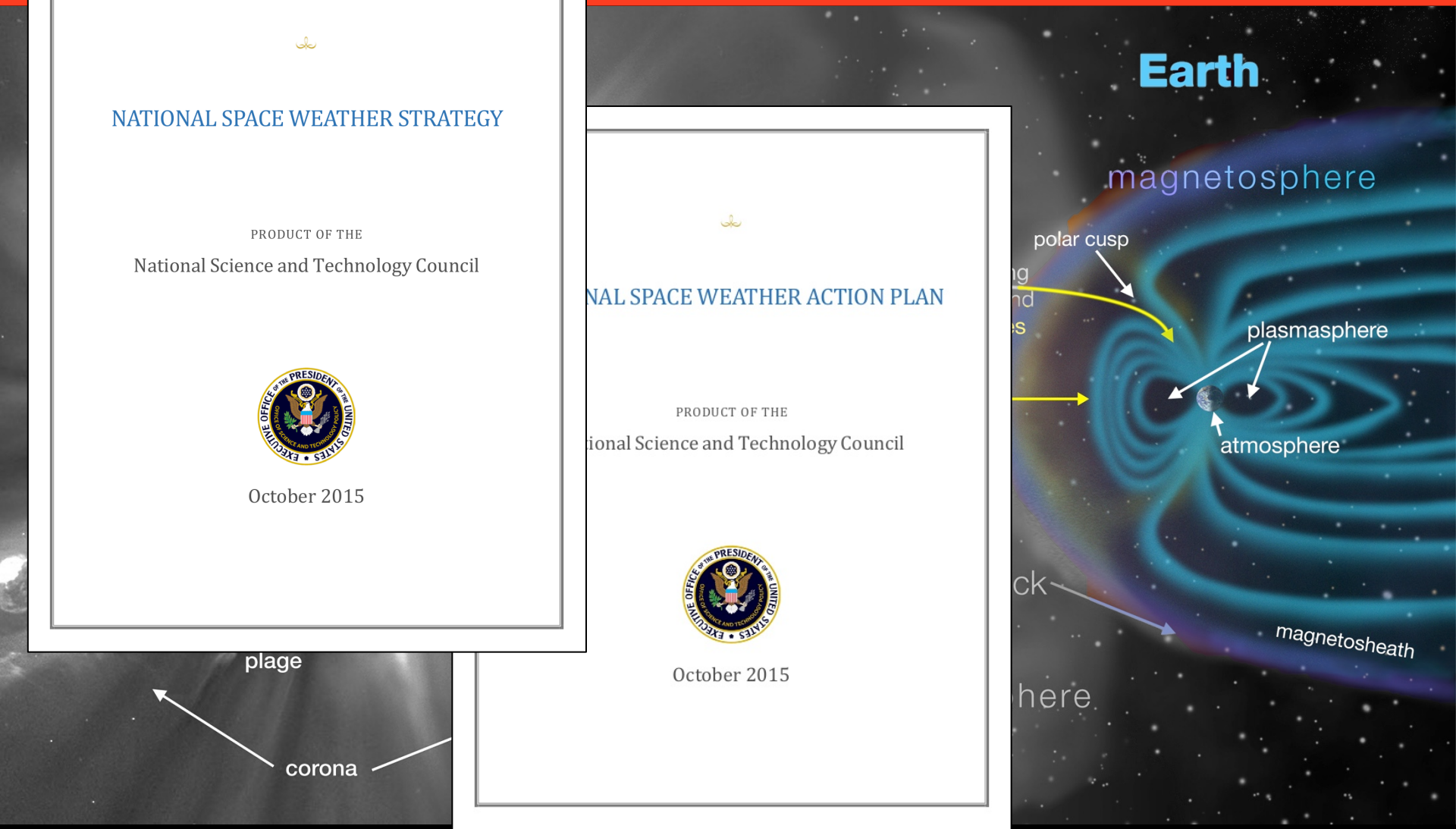

What is space weather?

Extended in *Space Weather Forecasting Act* (2017) - Bipartisan(?!) support

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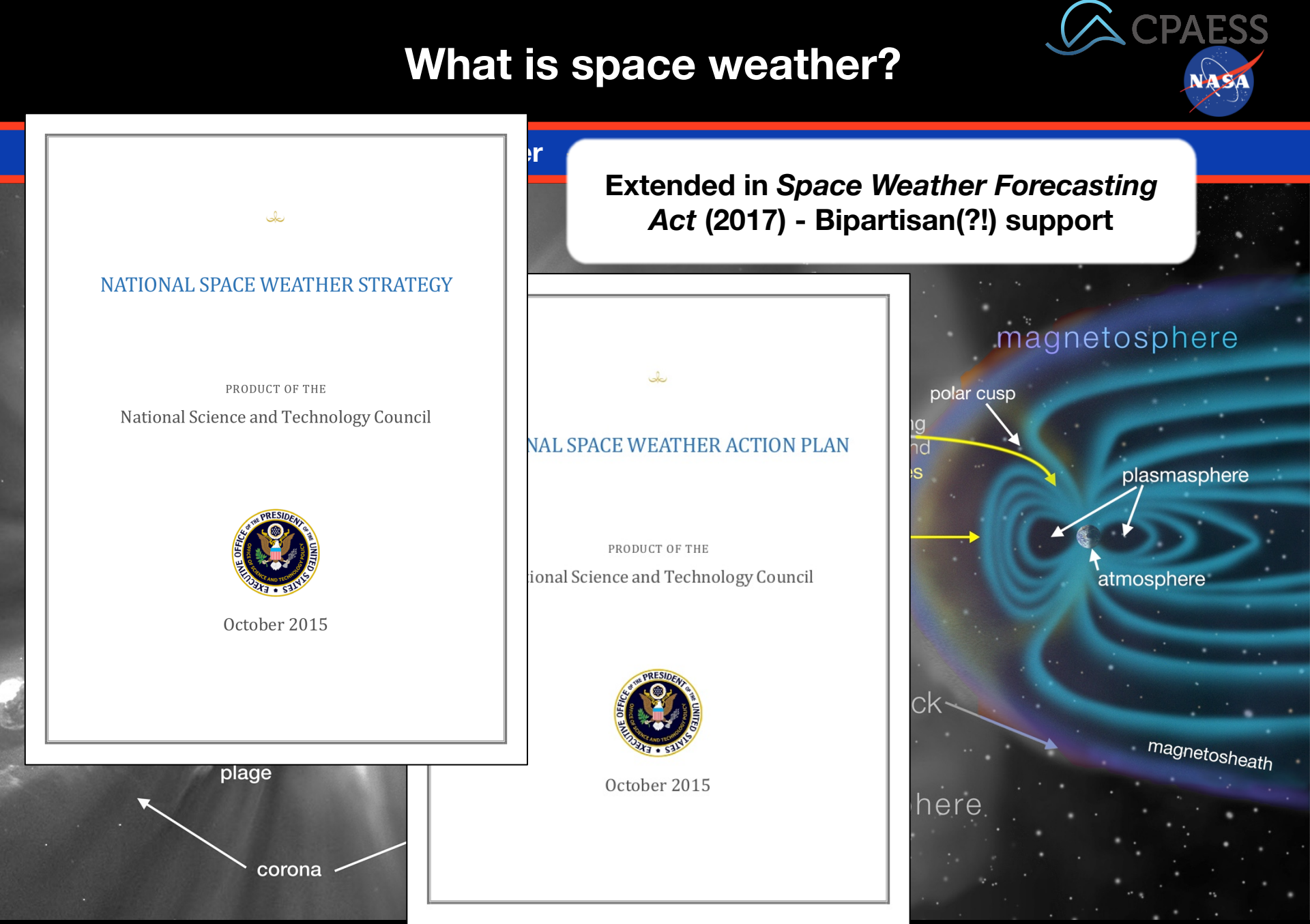
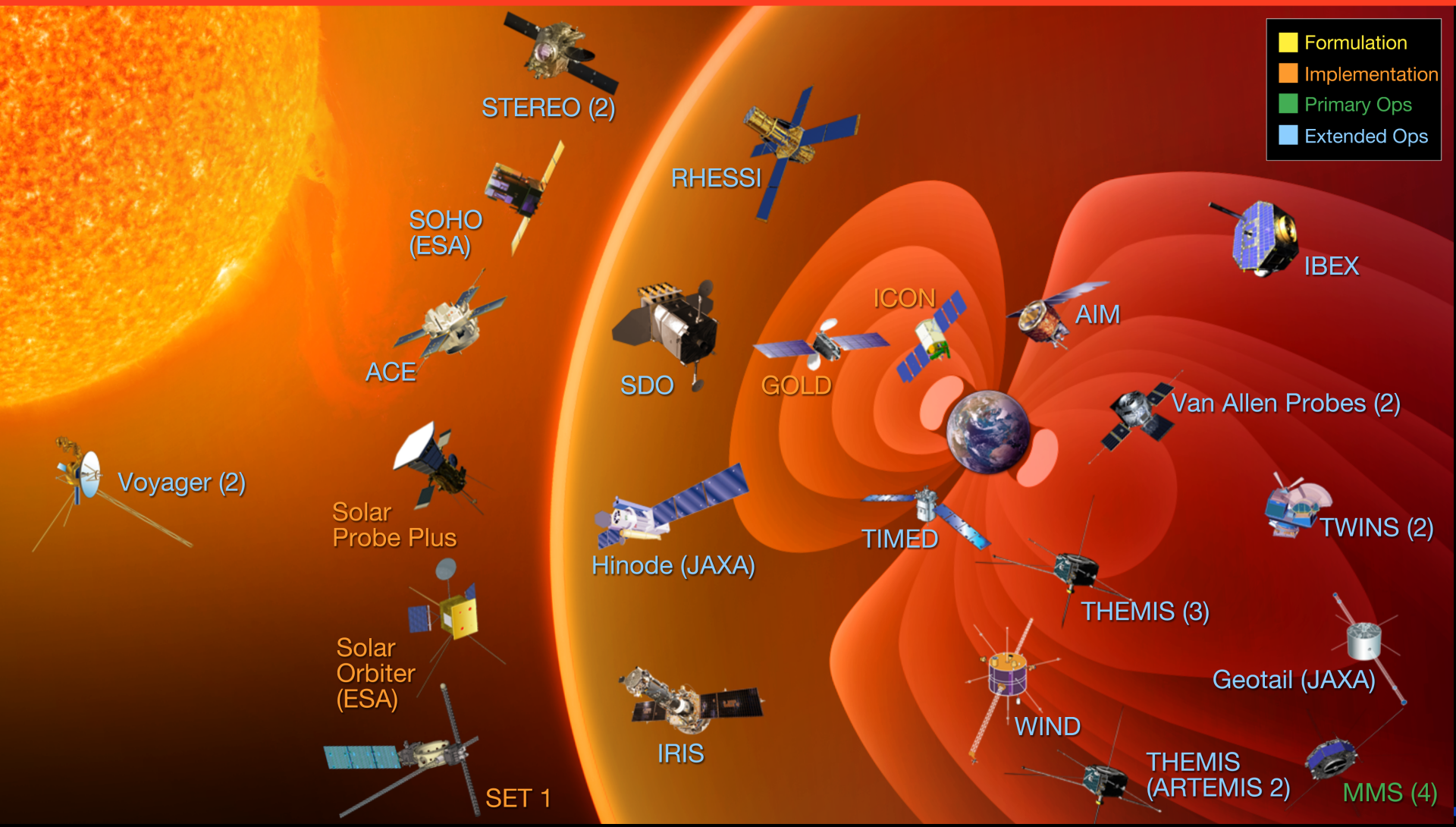


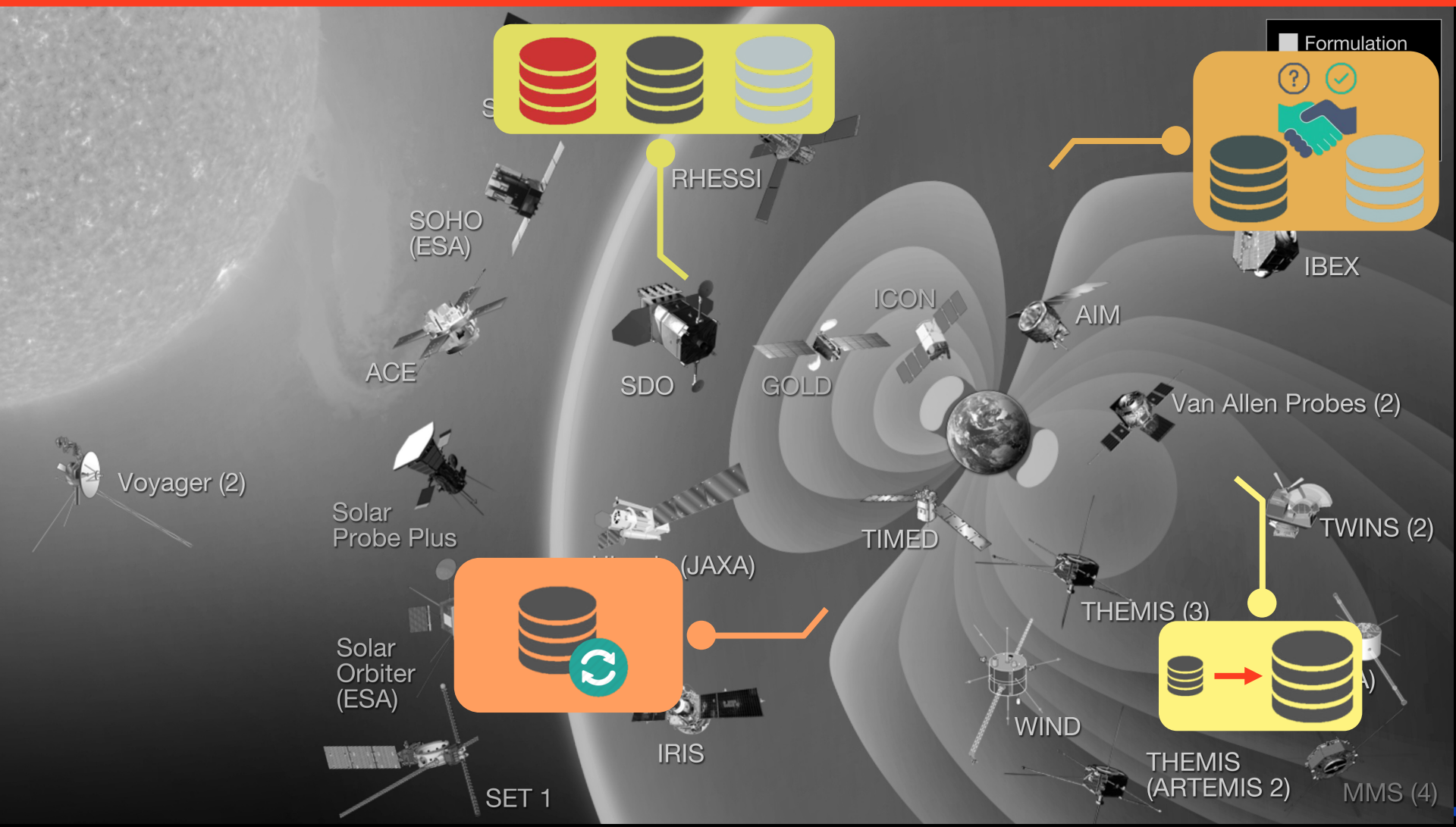
CPAESS

NASA

Heliophysics & space weather - Data-driven space weather - Exciting future



Heliophysics & space weather - Data-driven space weather - Exciting future

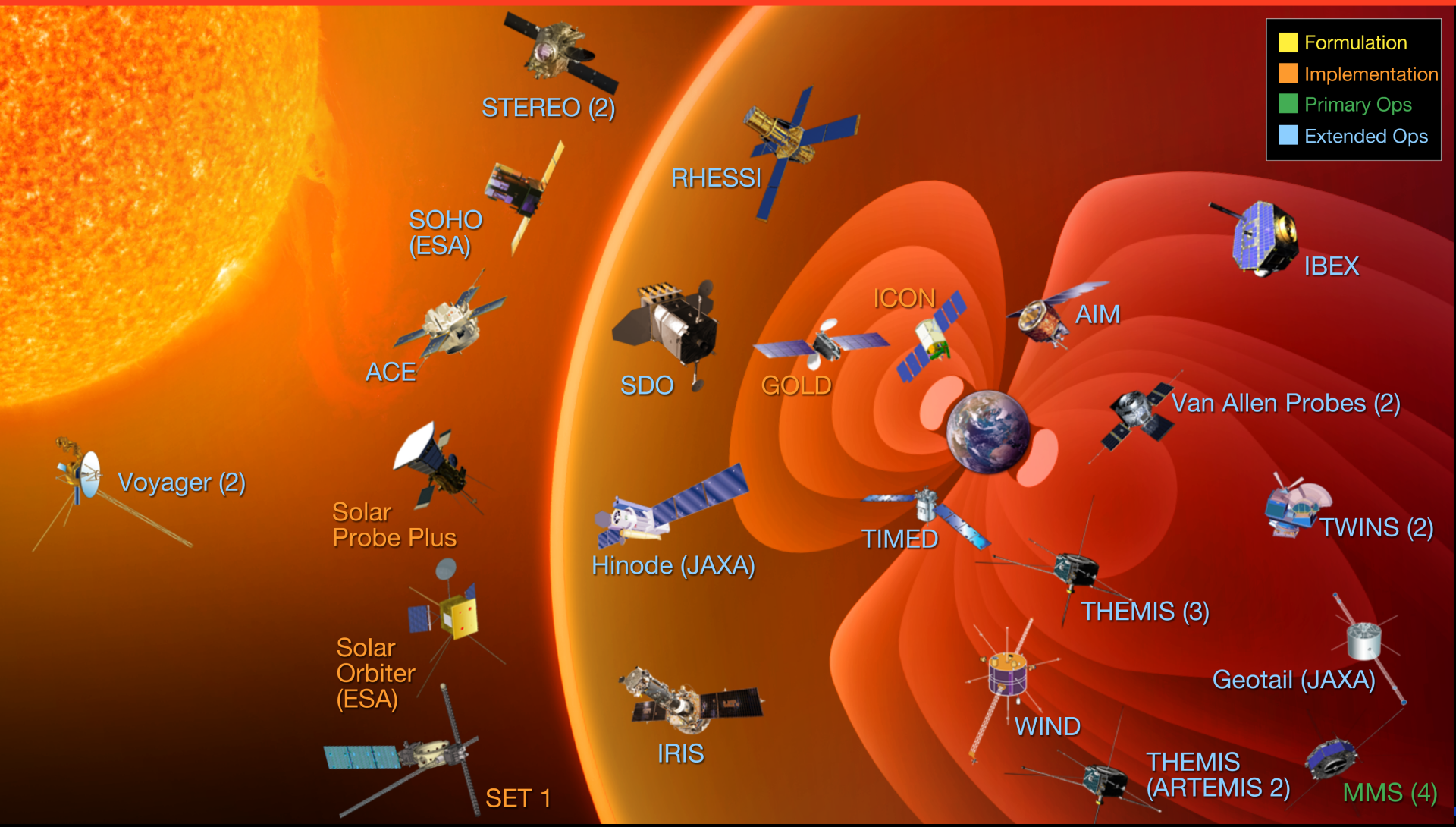


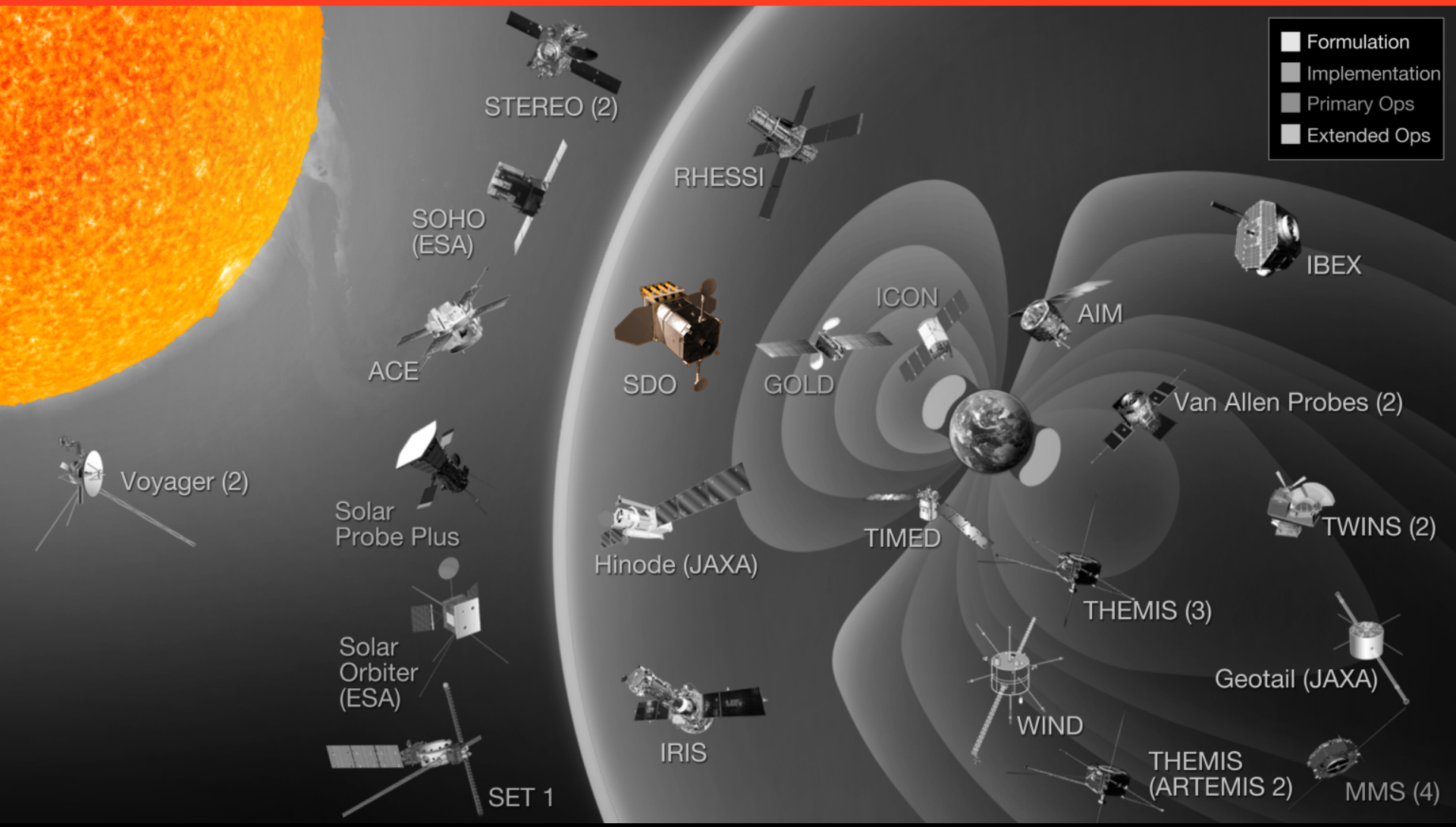
Universal challenges:

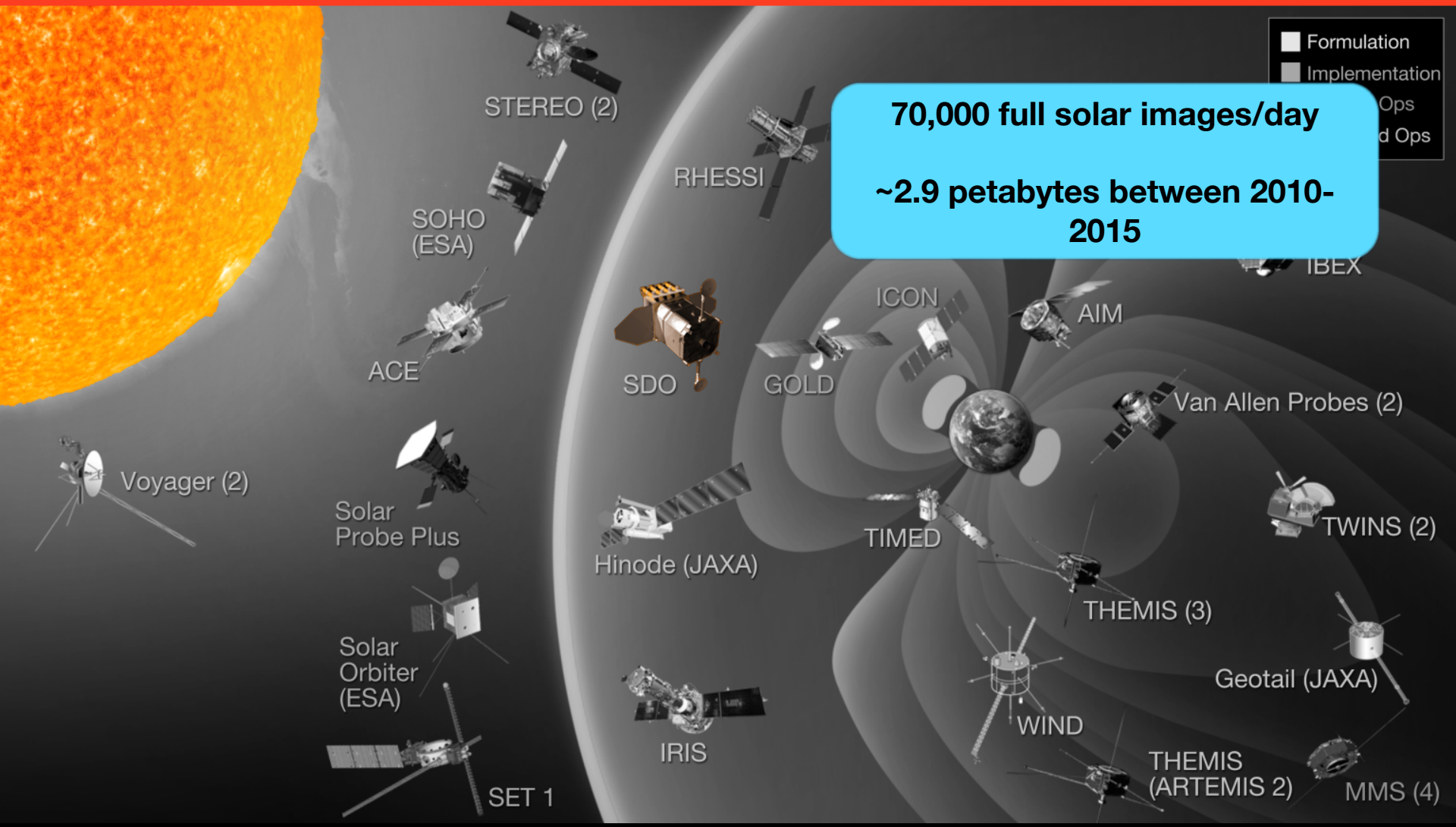
- Evolve traditional approaches
- Embrace data-driven discovery
- Enable interdisciplinary work

What if space weather were an exploration, data-driven science?

Heliophysics & space weather - **Data-driven space weather** - Exciting future




Formulation
Implementation
Primary Ops
Extended Ops
STEREO (2)
RHESSI
SOHO (ESA)
IBEX
ICON
AIM
ACE
SDO
GOLD
Van Allen Probes (2)
Voyager (2)
Solar Probe Plus
TWINS (2)
Hinode (JAXA)
TIMED
THEMIS (3)
Solar Orbiter (ESA)
Geotail (JAXA)
WIND
IRIS
THEMIS (ARTEMIS 2)
MMS (4)
SET 1


Formulation
Implementation
Ops
d Ops
70,000 full solar images/day
~2.9 petabytes between 2010-2015
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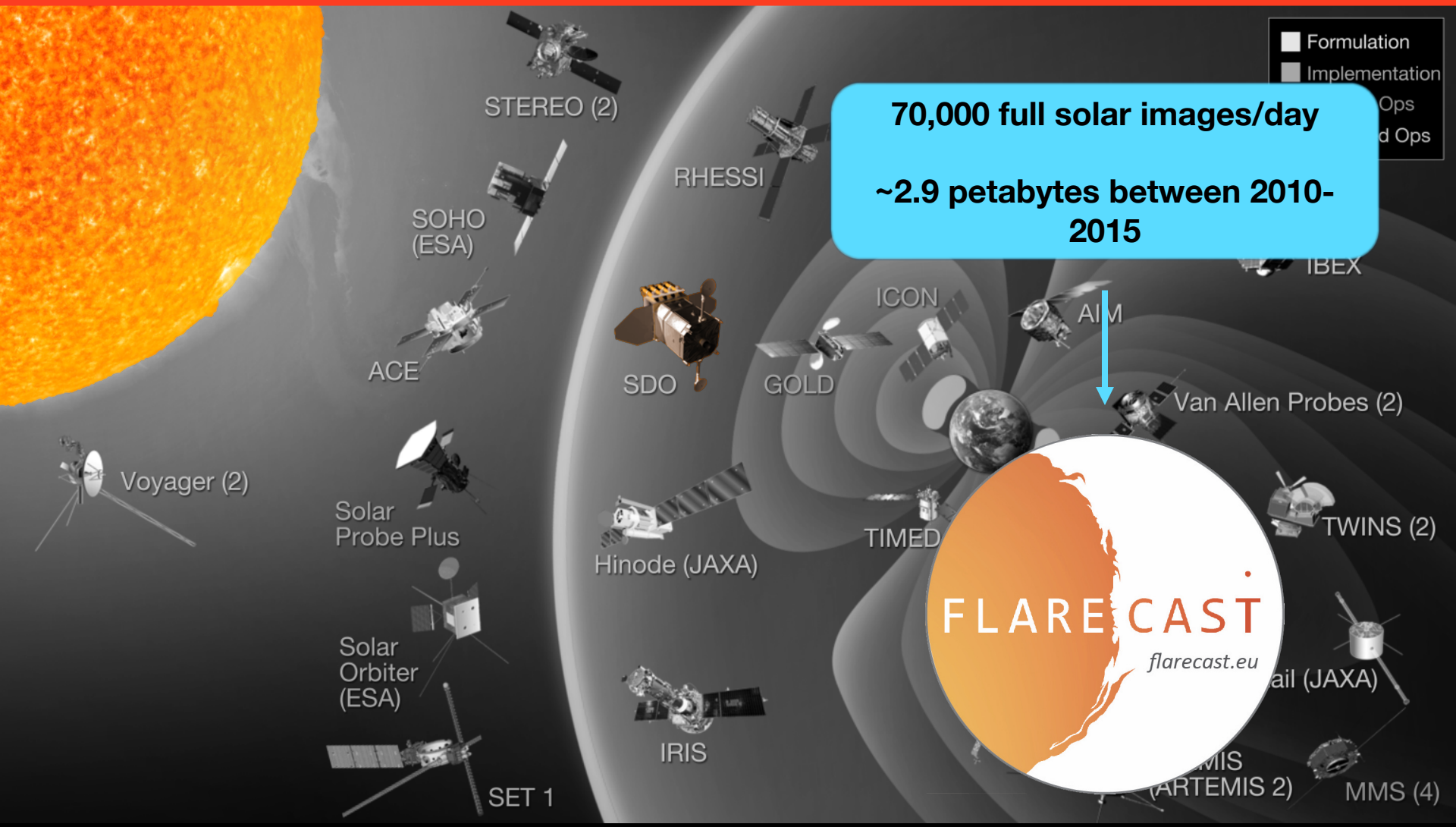
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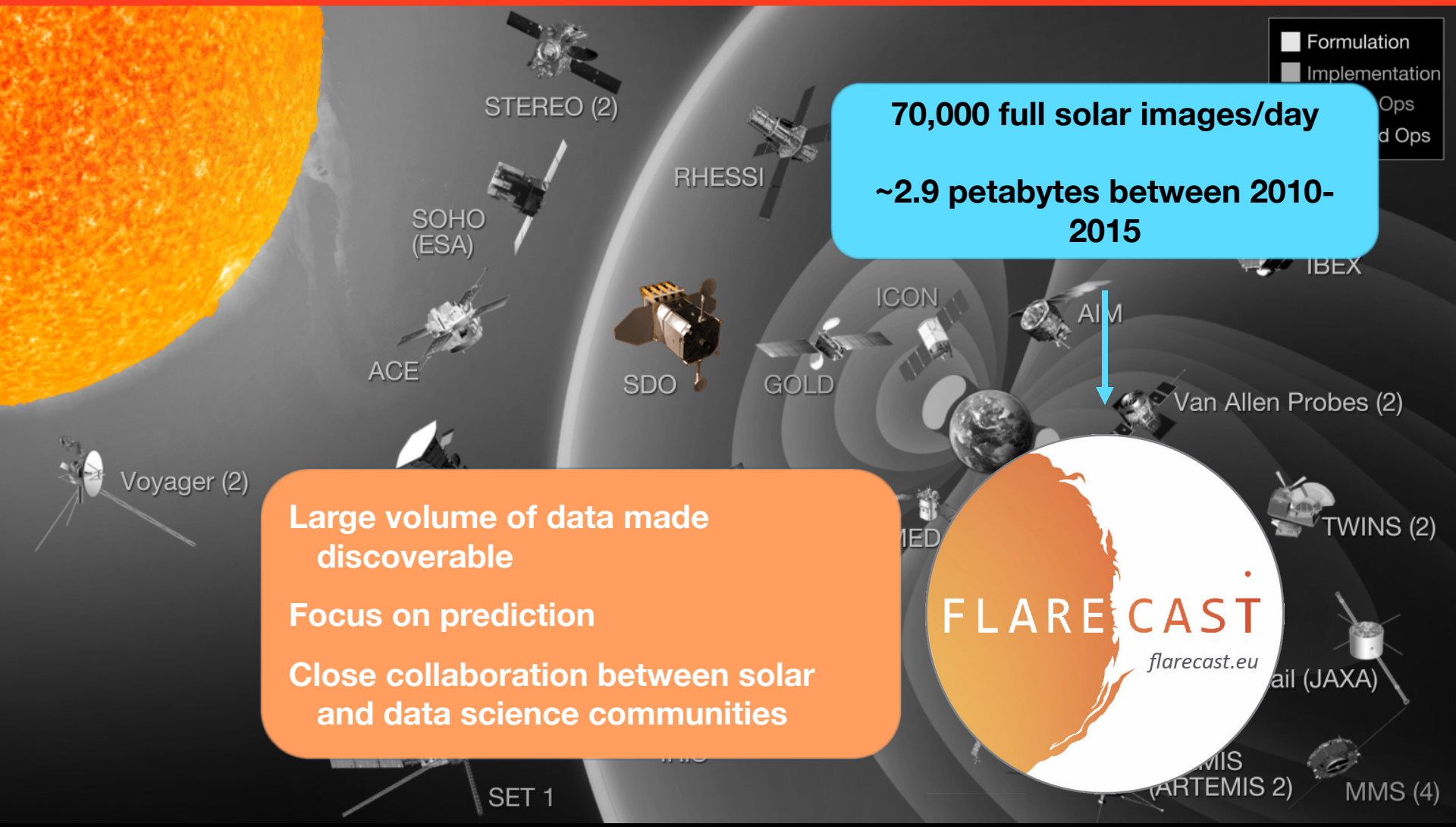
MMS (4)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SET 1
(ARTEMIS 2)
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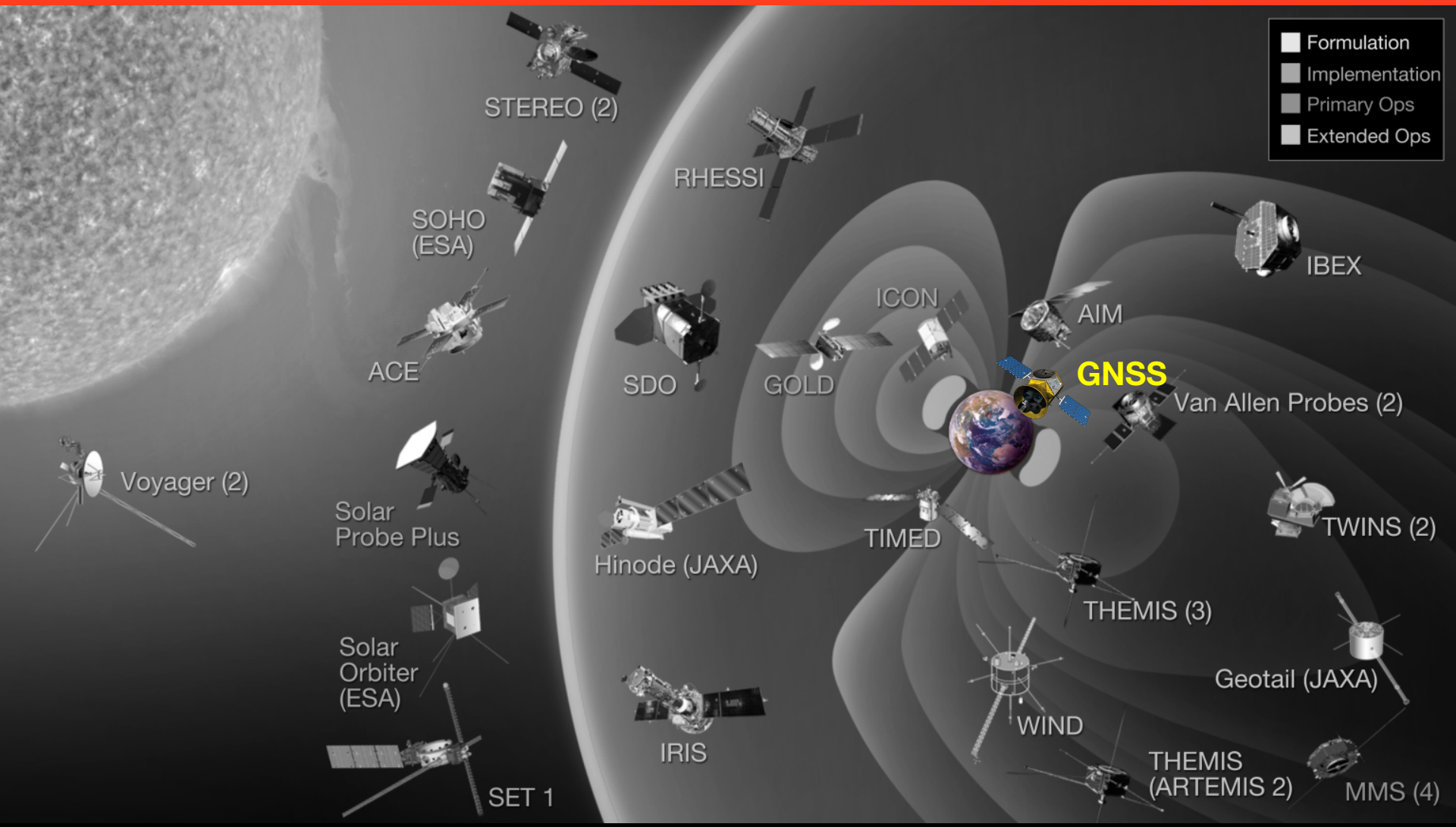
Large volume of data made discoverable
Focus on prediction
Close collaboration between solar and data science communities
FLARECAST
flarecast.eu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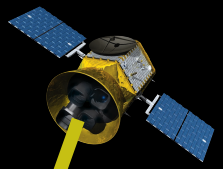
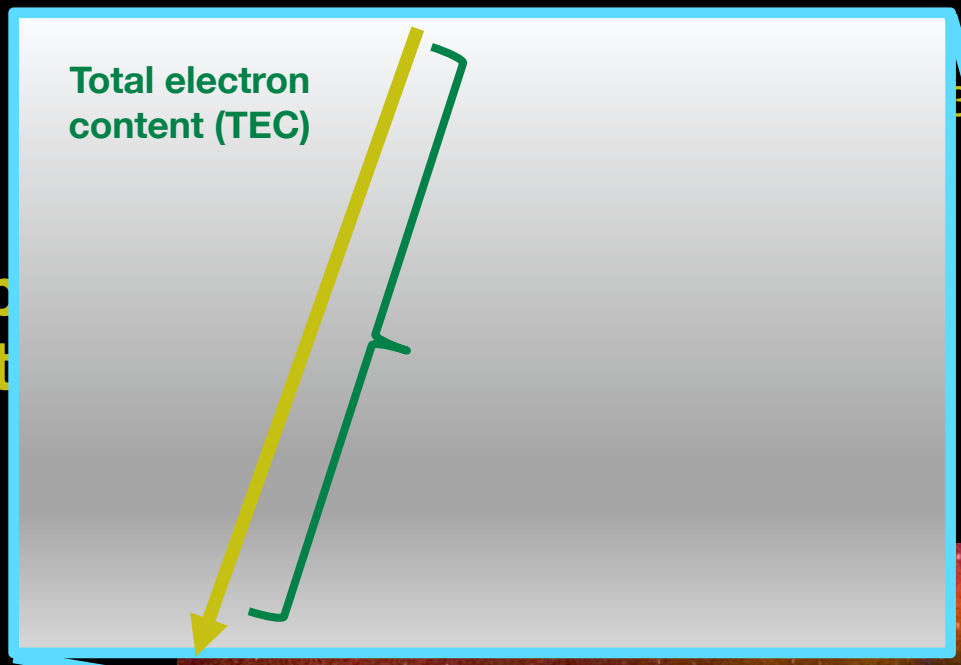
~6.6 Earth radii
(20,230 km altitude)

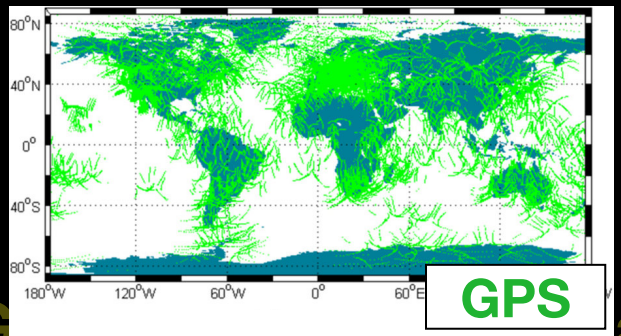


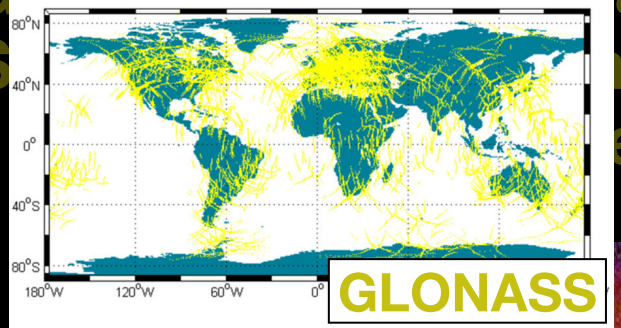
Global Navigation Satellite System (GNSS) signals for Space Science

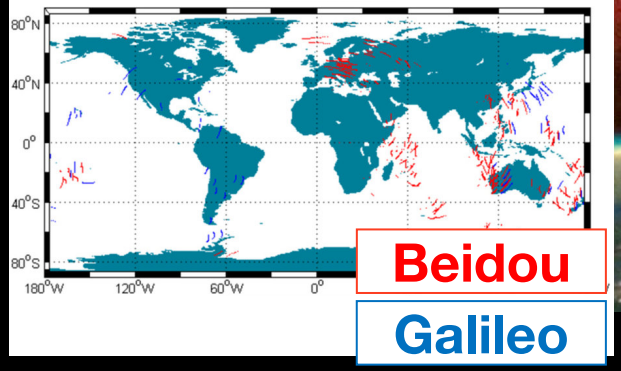
Glob
Syst



6 Earth radii
0 km altitude)







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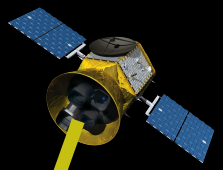
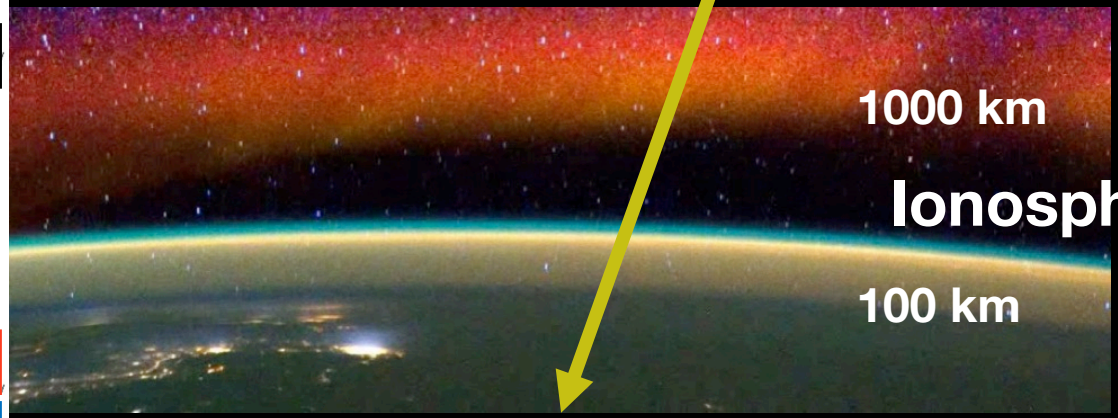
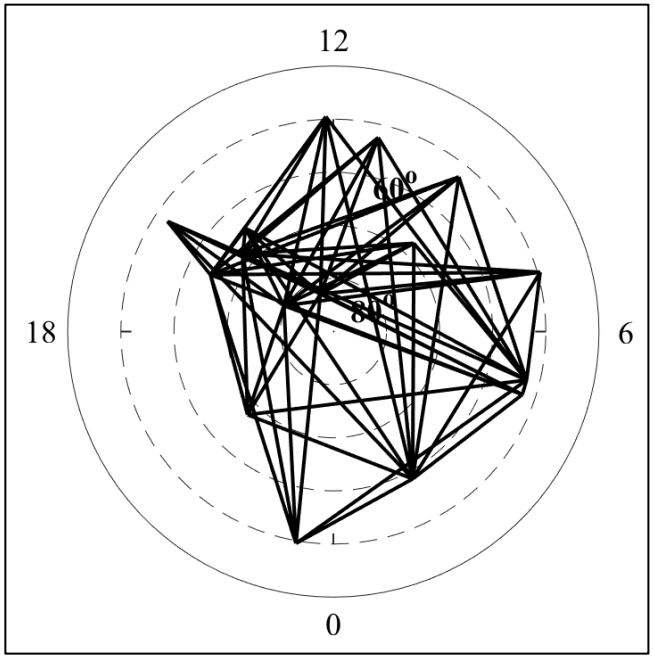


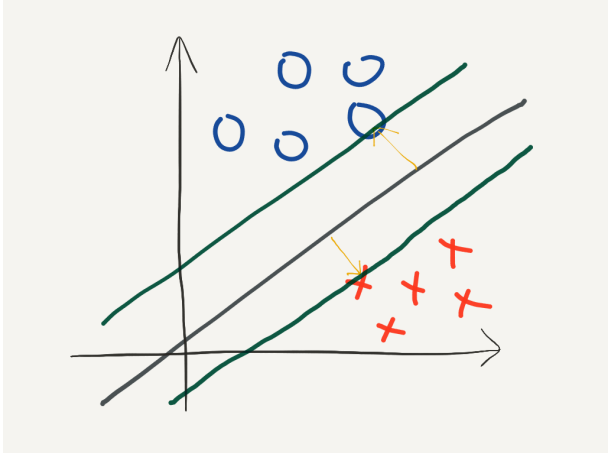


Data-driven space weather

Two highlights

1 **Novel approach to space weather discovery: Network Analysis**

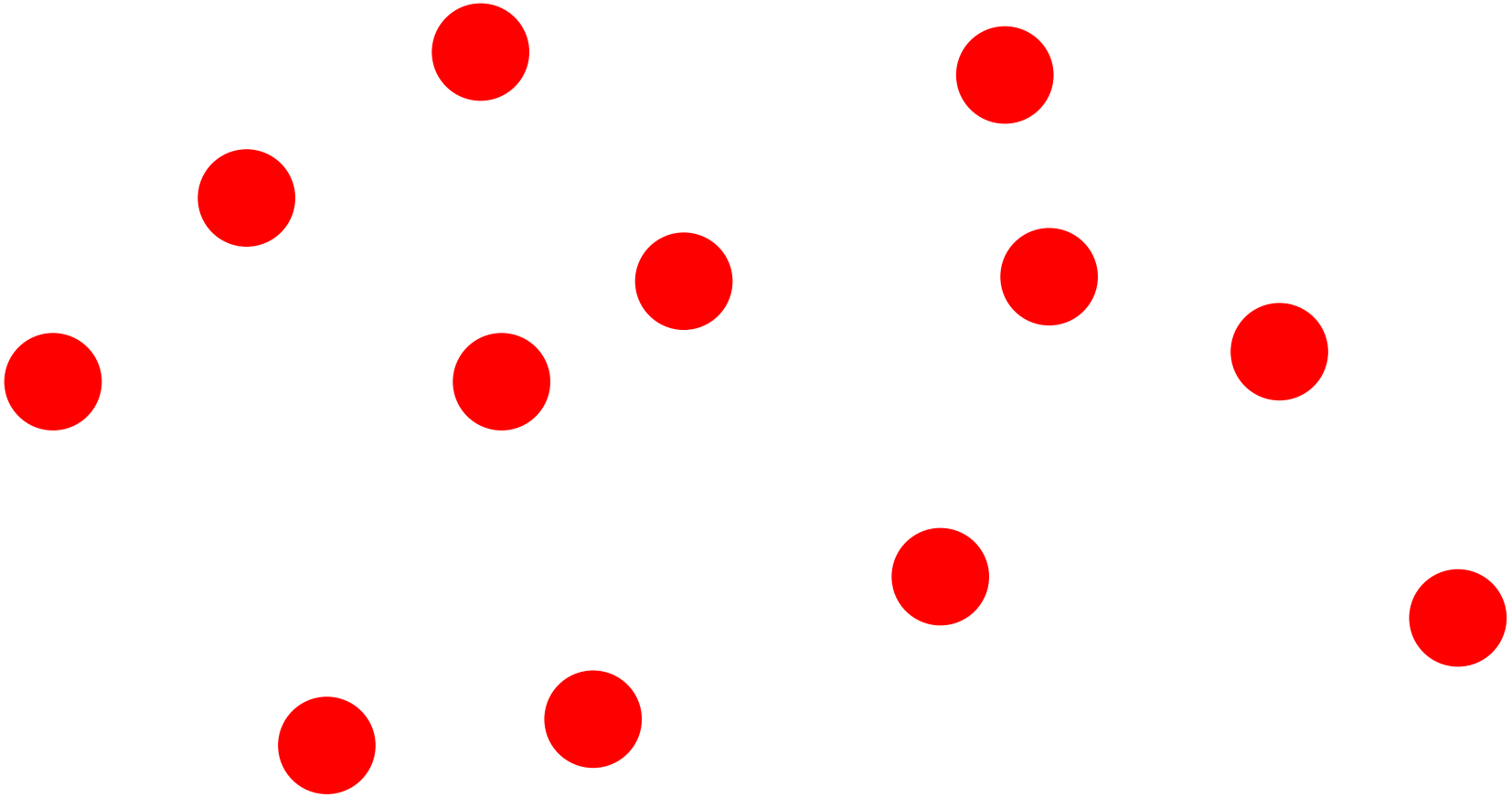




2 **Machine learning for space weather prediction**

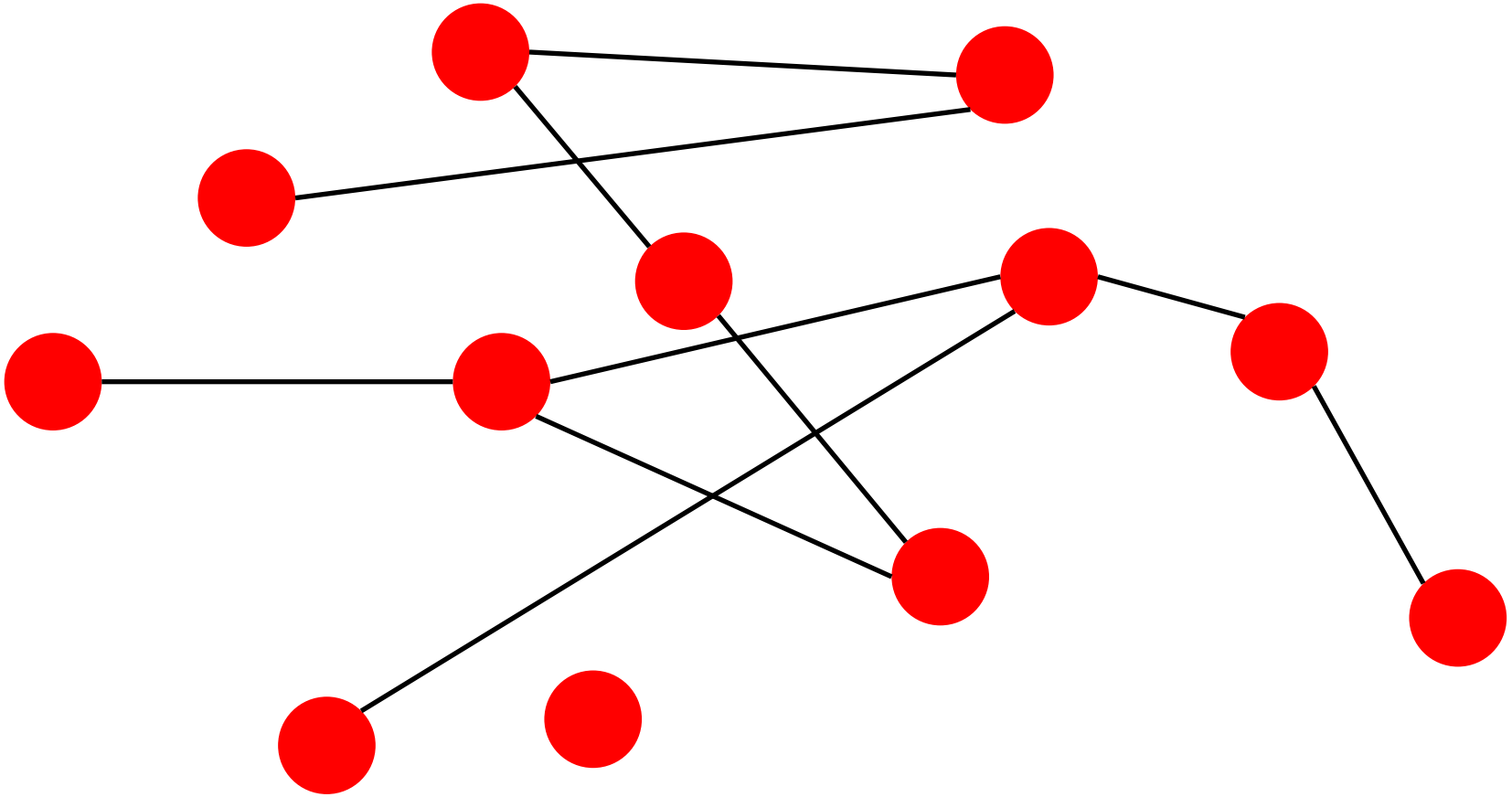
Data-driven space weather:
Network analysis

What is network analysis?



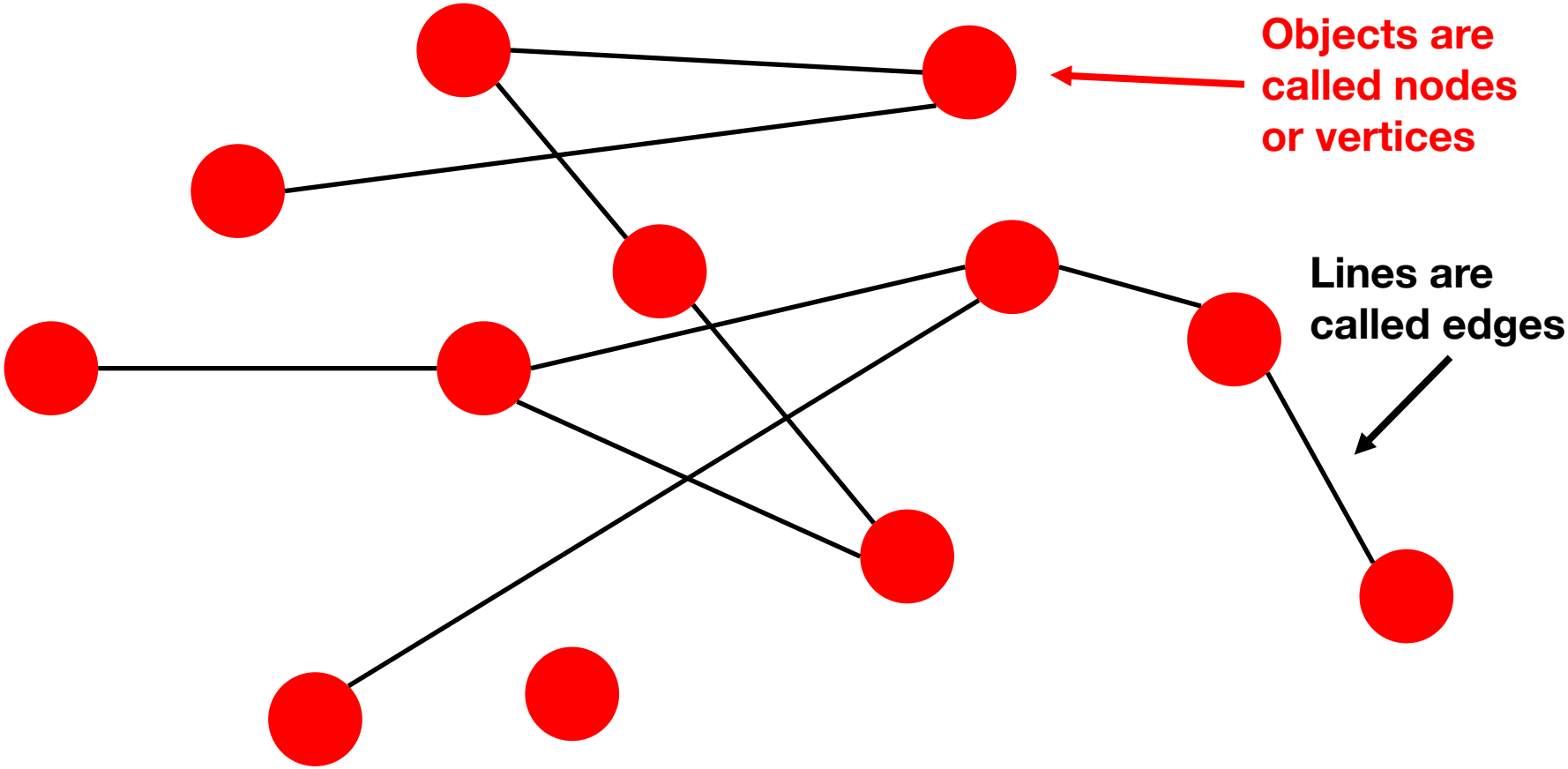
Collection of 'objects'

What is network analysis?

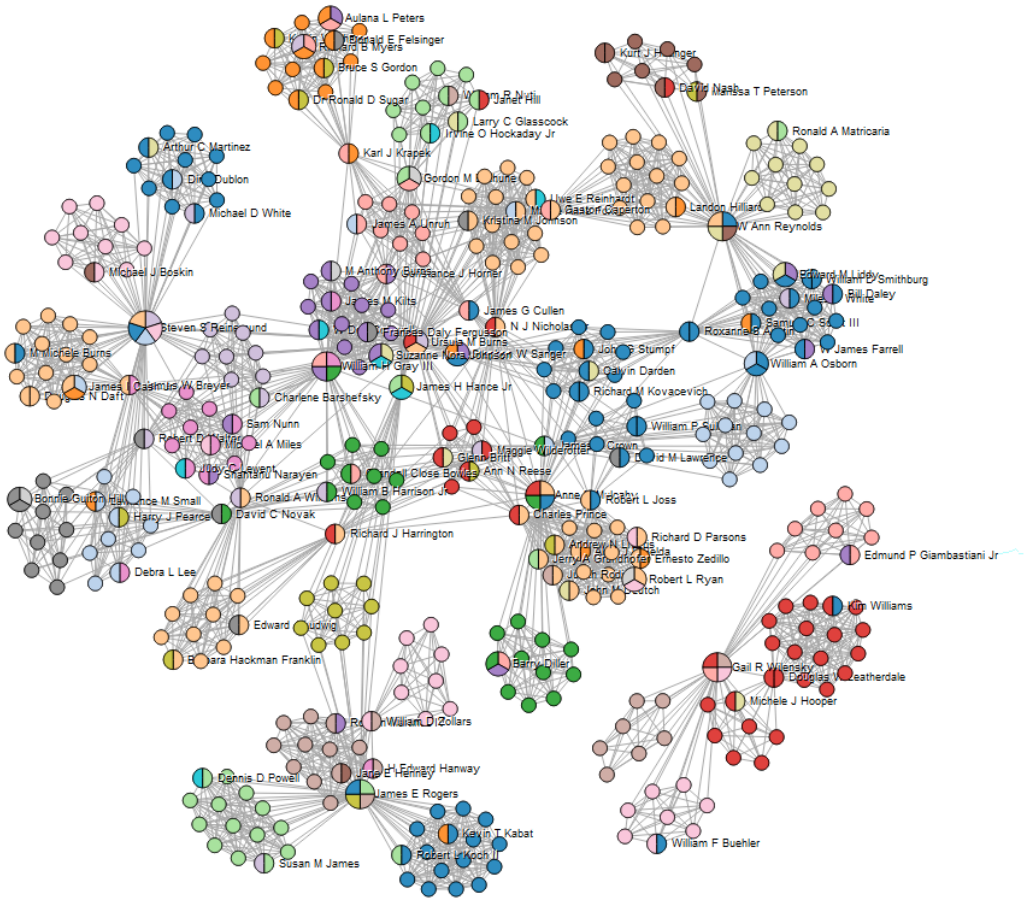


Objects are connected by lines

What is network analysis?

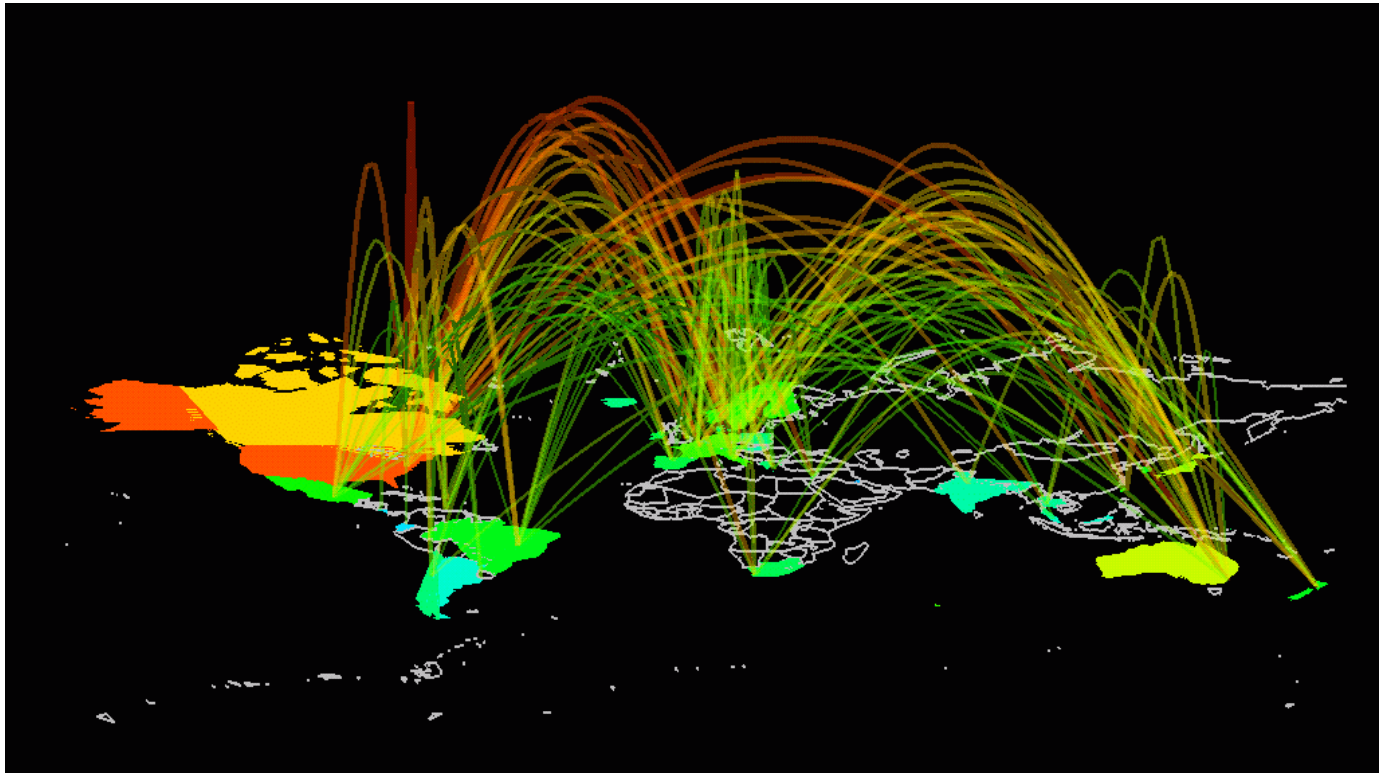


Examples of networks:
Social network



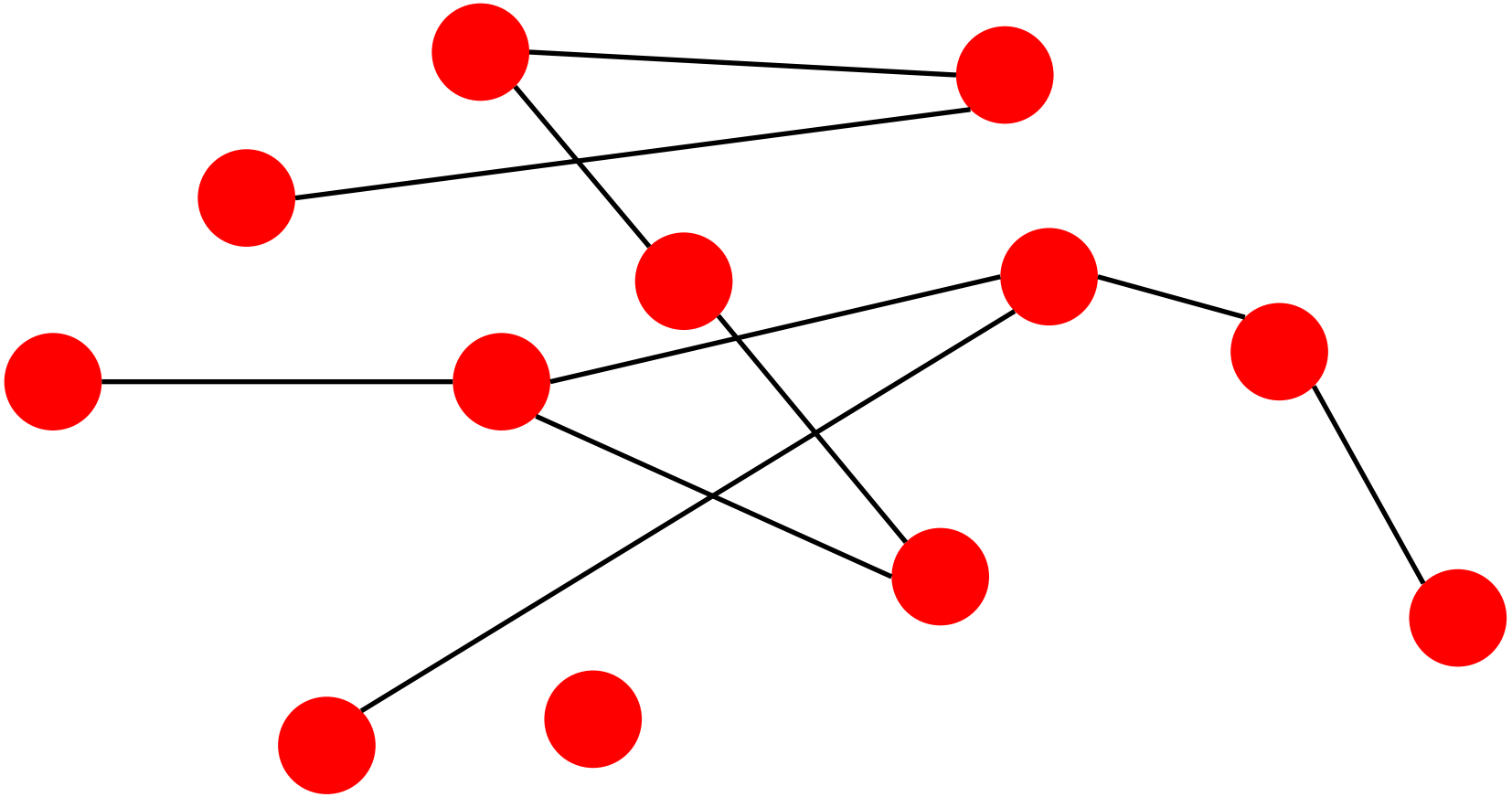
OrgPedia corporate board network (https://bulaza.wordpress.com/)

Examples of networks:
Social network



Martin Dodge, University of Manchester

What is network analysis?



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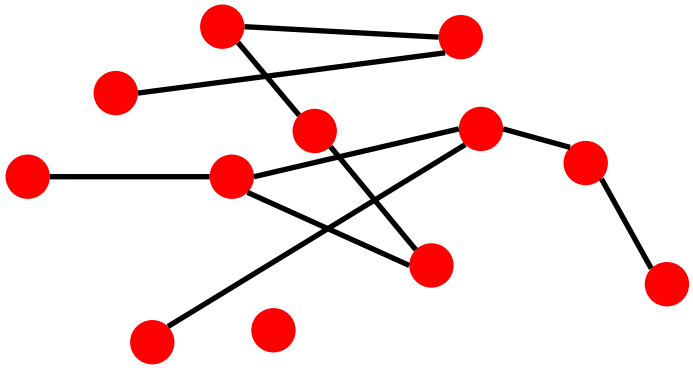
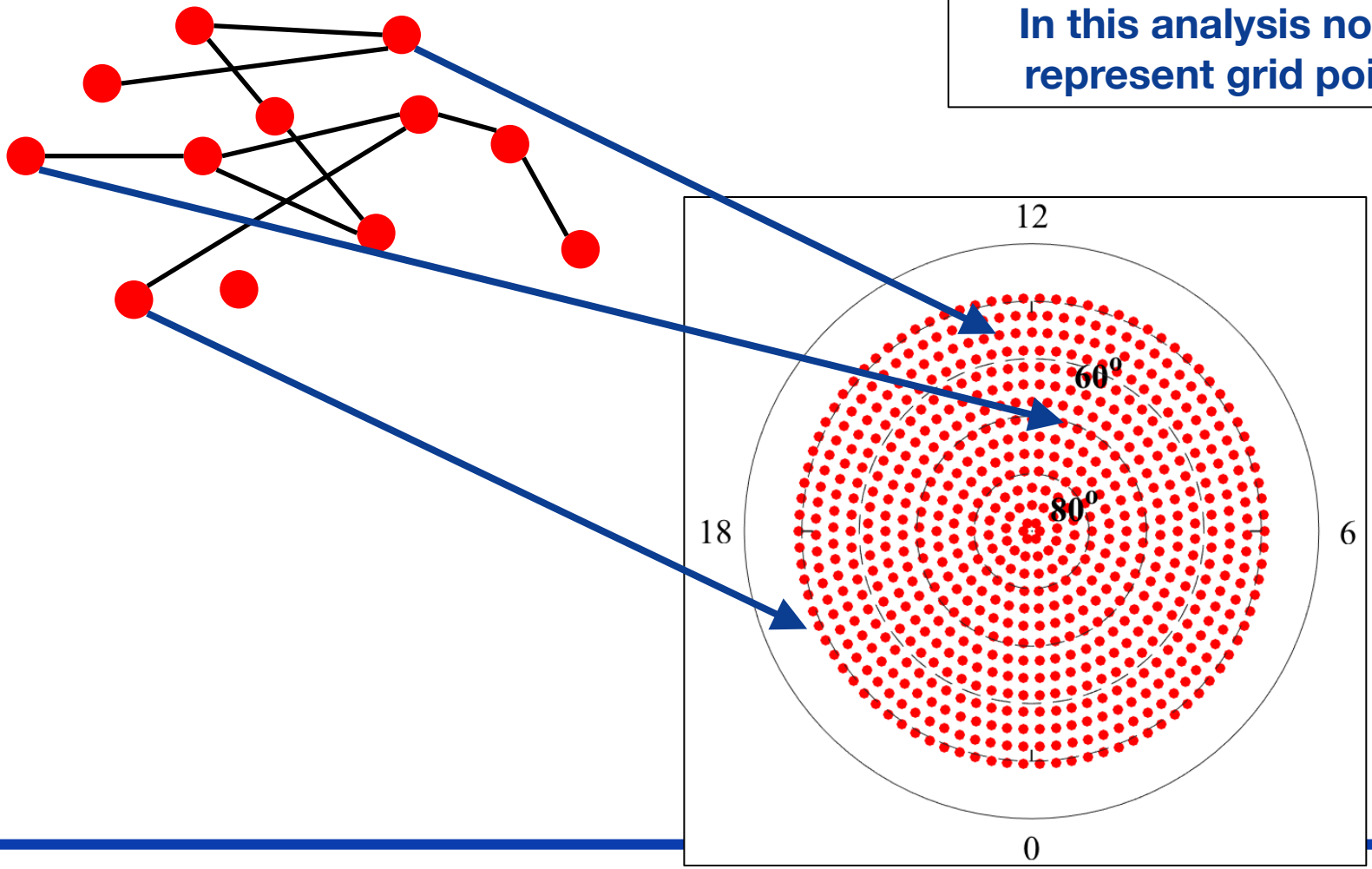


What is network analysis?

In this analysis nodes represent grid points



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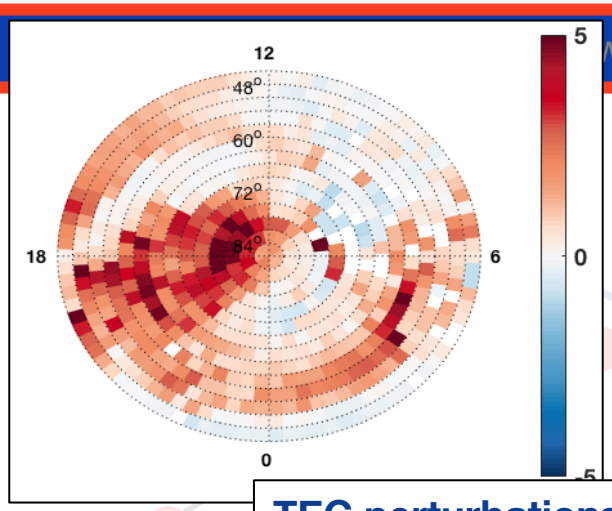
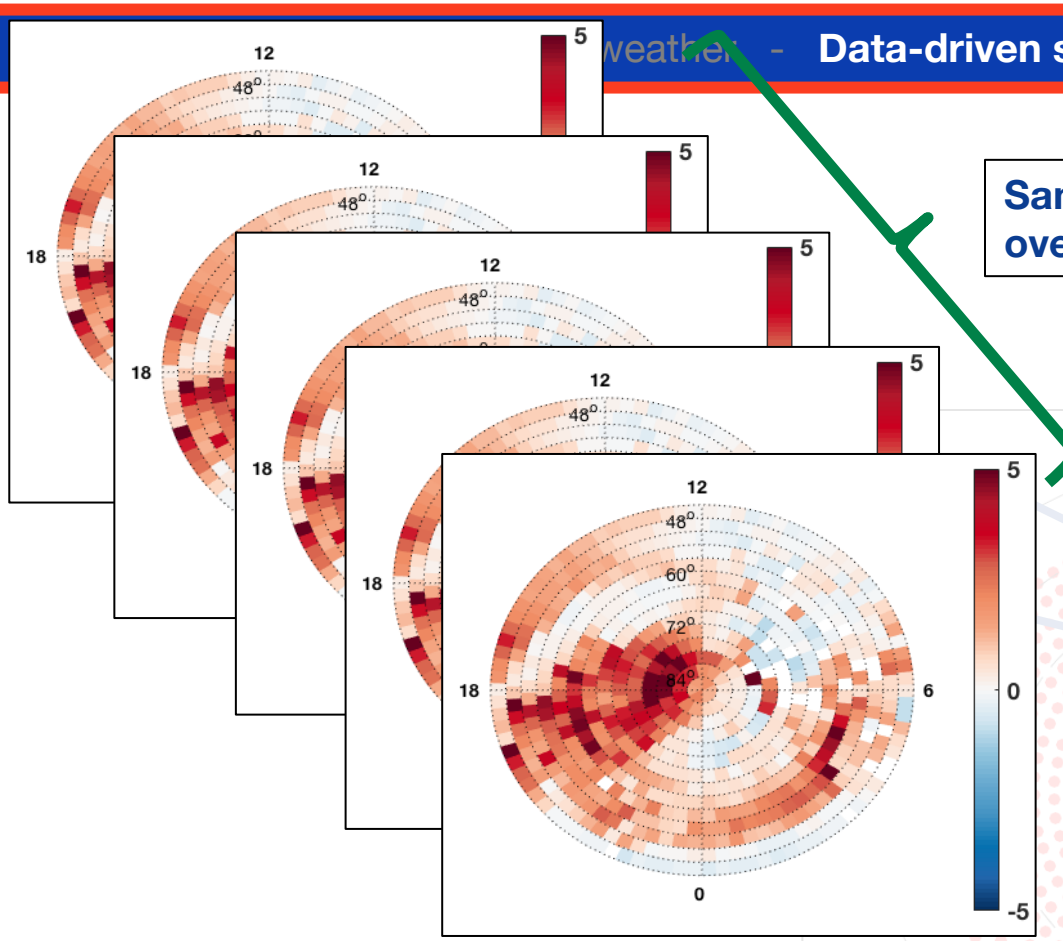


TEC perturbations from GNSS signal data

In this analysis nodes represent grid points

What is network analysis?

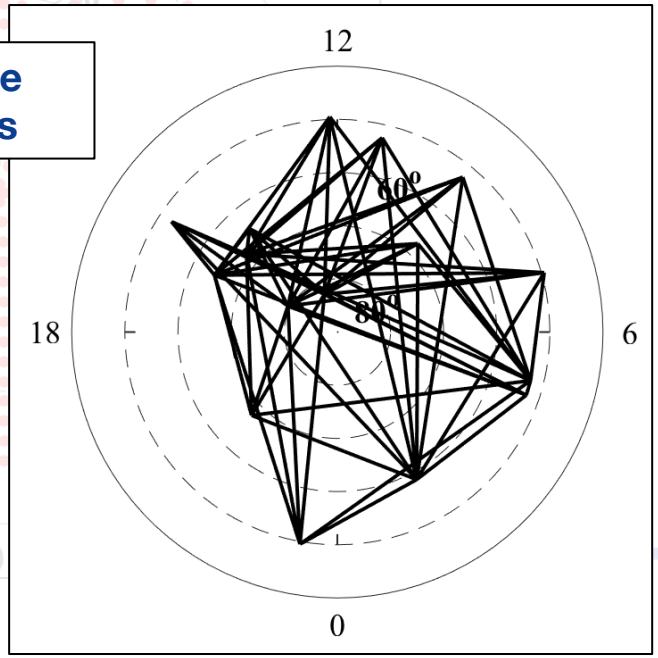


Samples collected over time

What is network analysis?

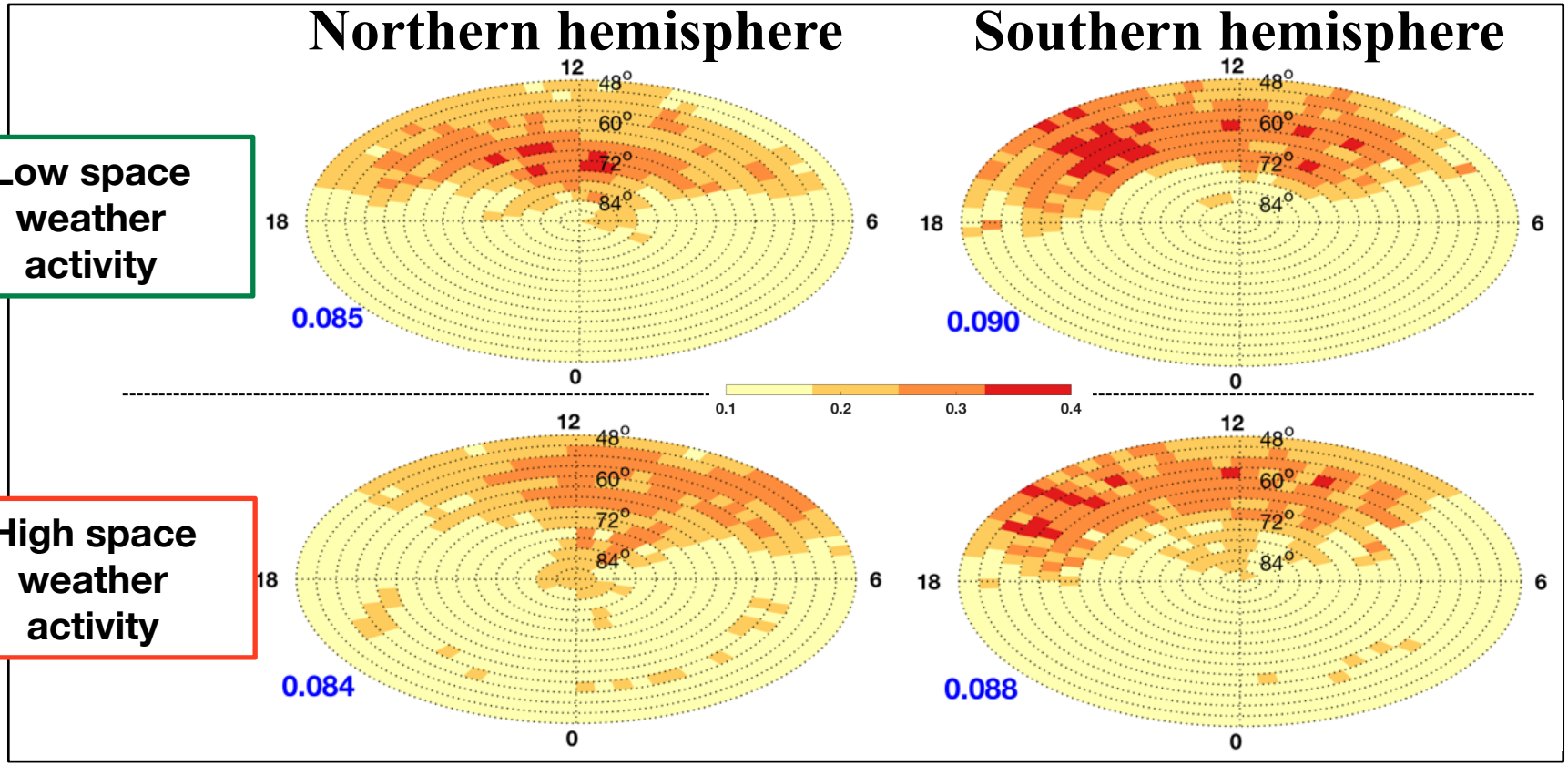
In this analysis nodes represent grid points

Visualize the connections



Network analysis

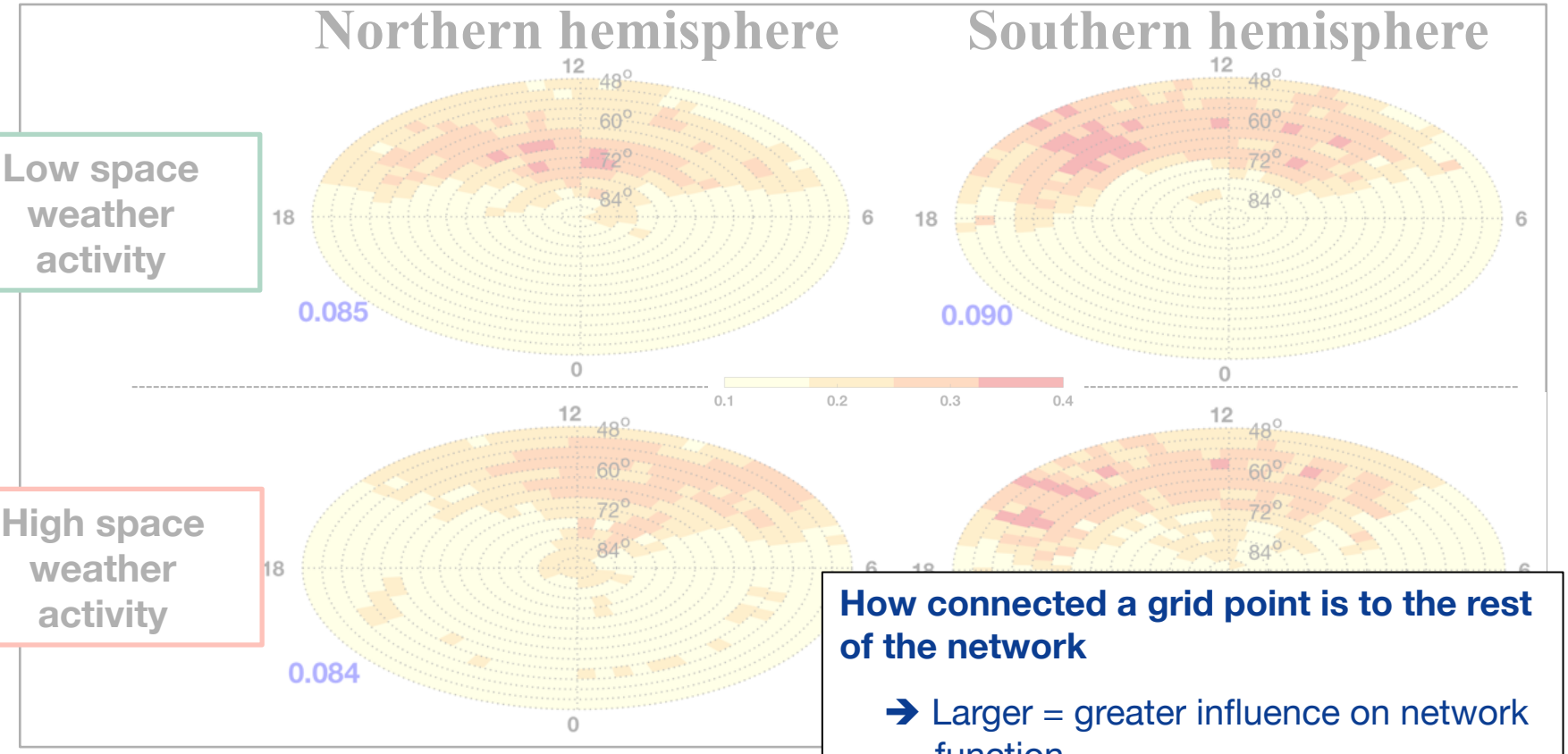
Degree Centrality



McGranaghan, R. M., A. J. Mannucci, O. Verkhoglyadova, and N. Malik (2017), Finding multiscale connectivity in our geospace observational system: Network analysis of total electron content, J. Geophys. Res. Space Physics, 122, doi:10.1002/2017JA024202.

Network analysis

Degree Centrality

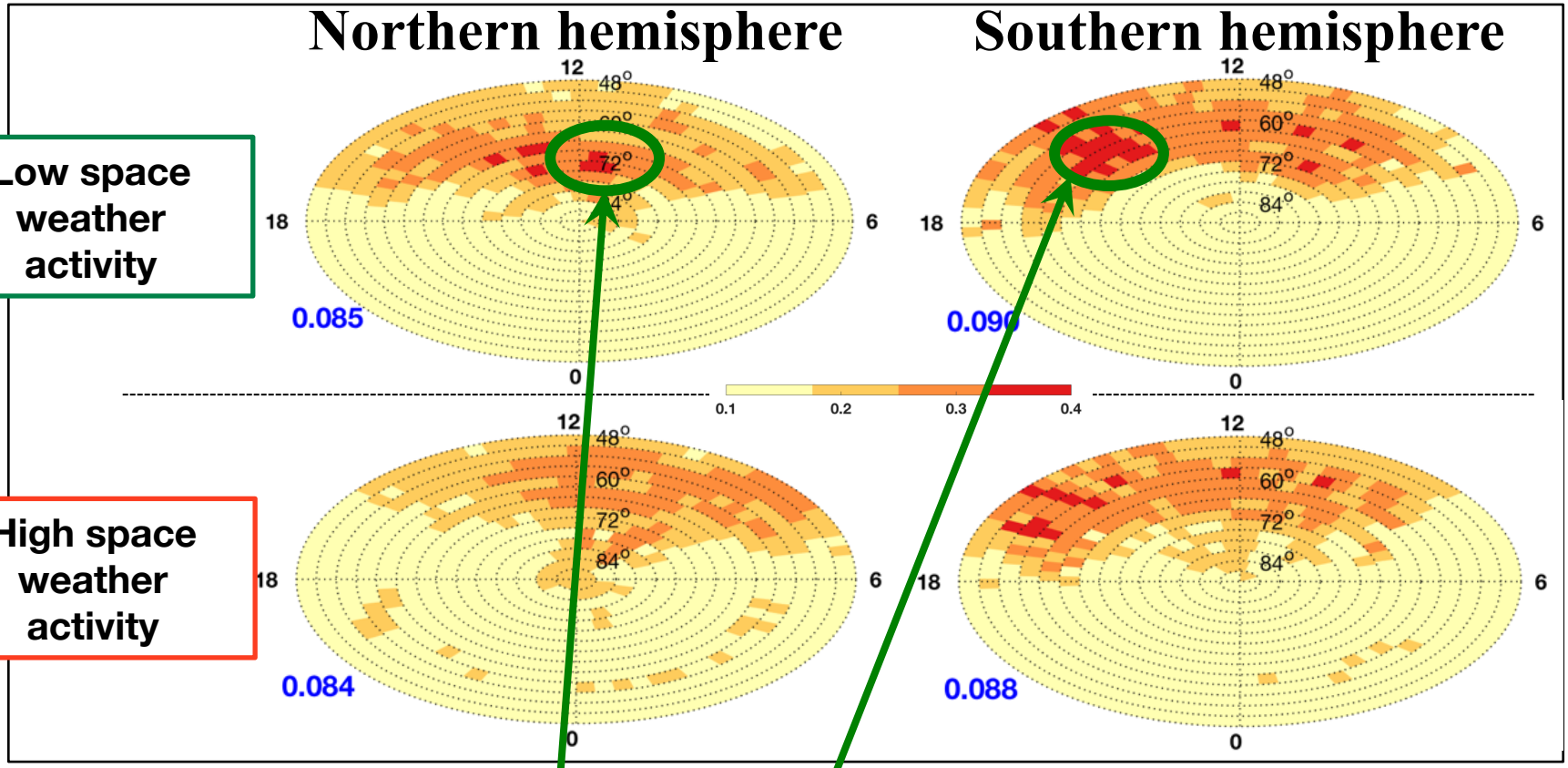


How connected a grid point is to the rest of the network

➔ Larger = greater influence on network function

Network analysis

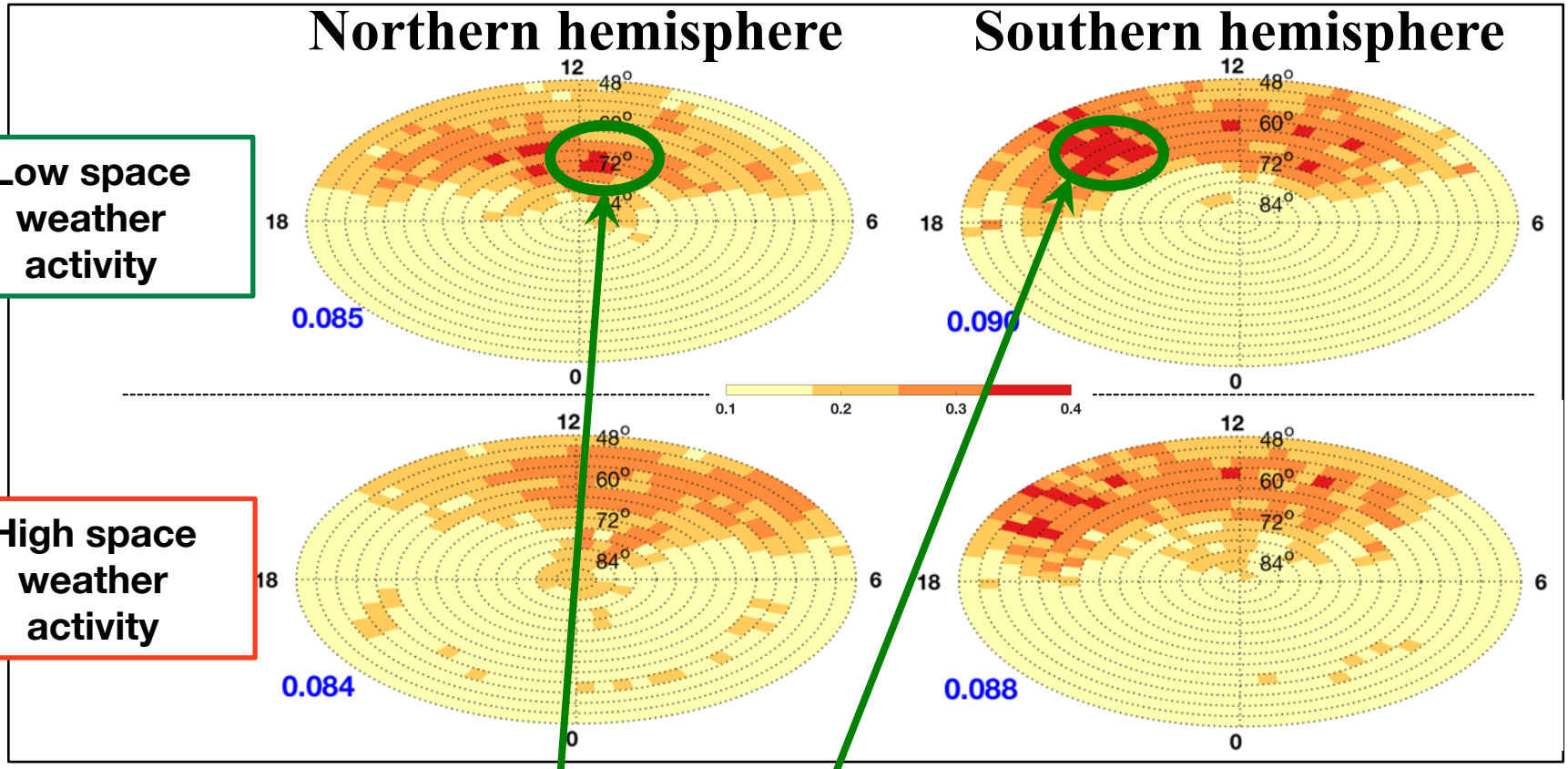
Degree Centrality



Critical locations of space weather activity emerge from the network measures

Network analysis

Degree Centrality

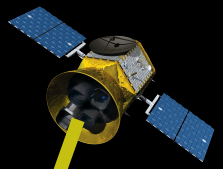


Critical locations of space weather activity emerge from the network measures

Network analysis provides new insight for space weather

Illustrative of potential for data-driven approaches to impact space weather

~6.6 Earth radii
(20,230 km altitude)



Global Navigation Satellite System (GNSS) signals for Space Science

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6 Earth radii
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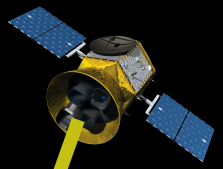

Scintillation
(signal disruption)

1000 km

Ionosphere

100 km

Data-driven space weather:
Machine learning

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Machine learning

Problems well-suited to machine learning

- Classification
- Event detection
- Clustering
- Prediction

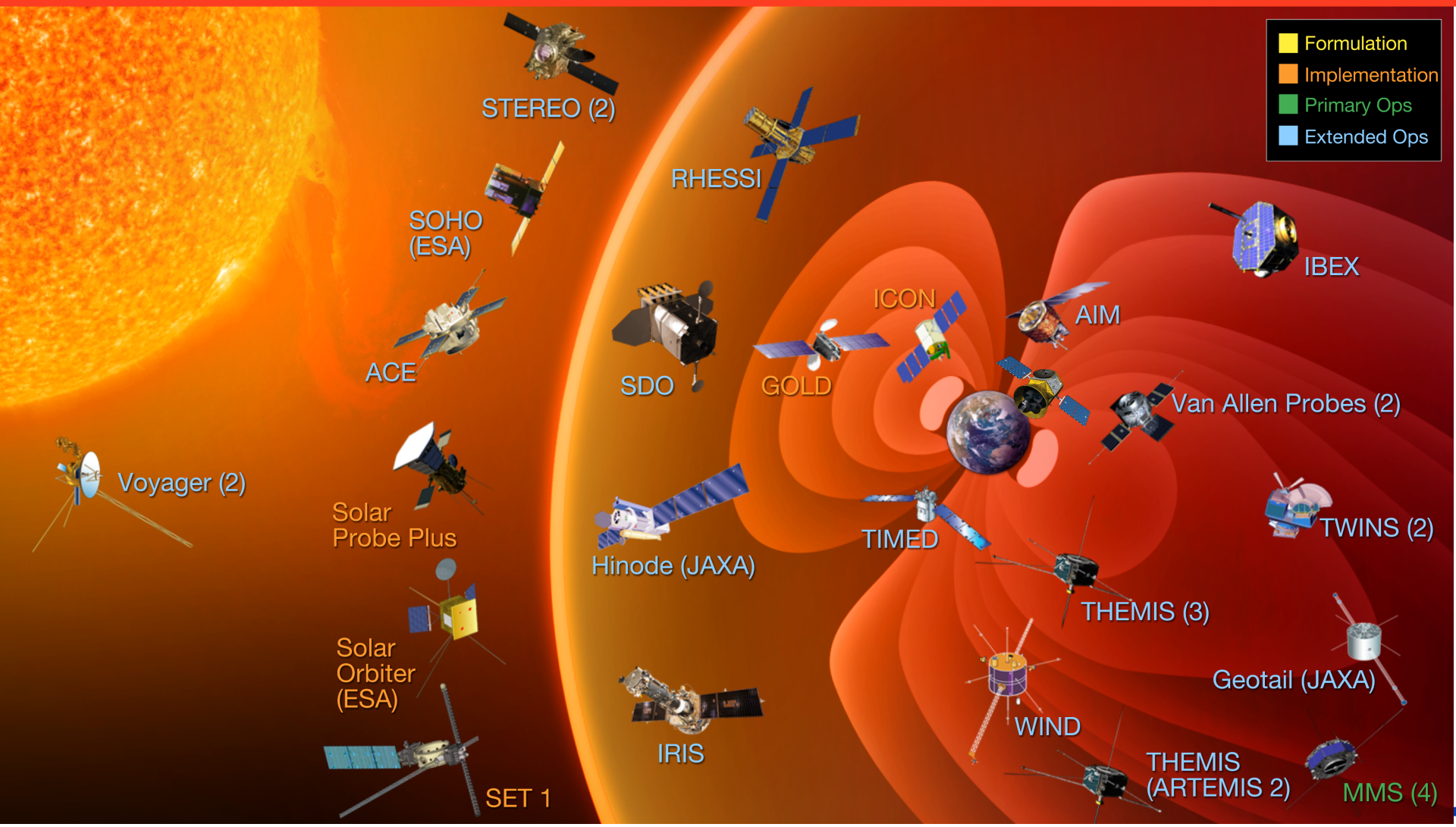
Data-driven space weather:
Machine learning

Problems well-suited to machine learning

- Classification
- Event detection
- Clustering
- **Prediction**

Step 1:
Obtain solar, geomagnetic, and ionospheric data

Heliophysics & space weather - **Data-driven space weather** - Exciting future



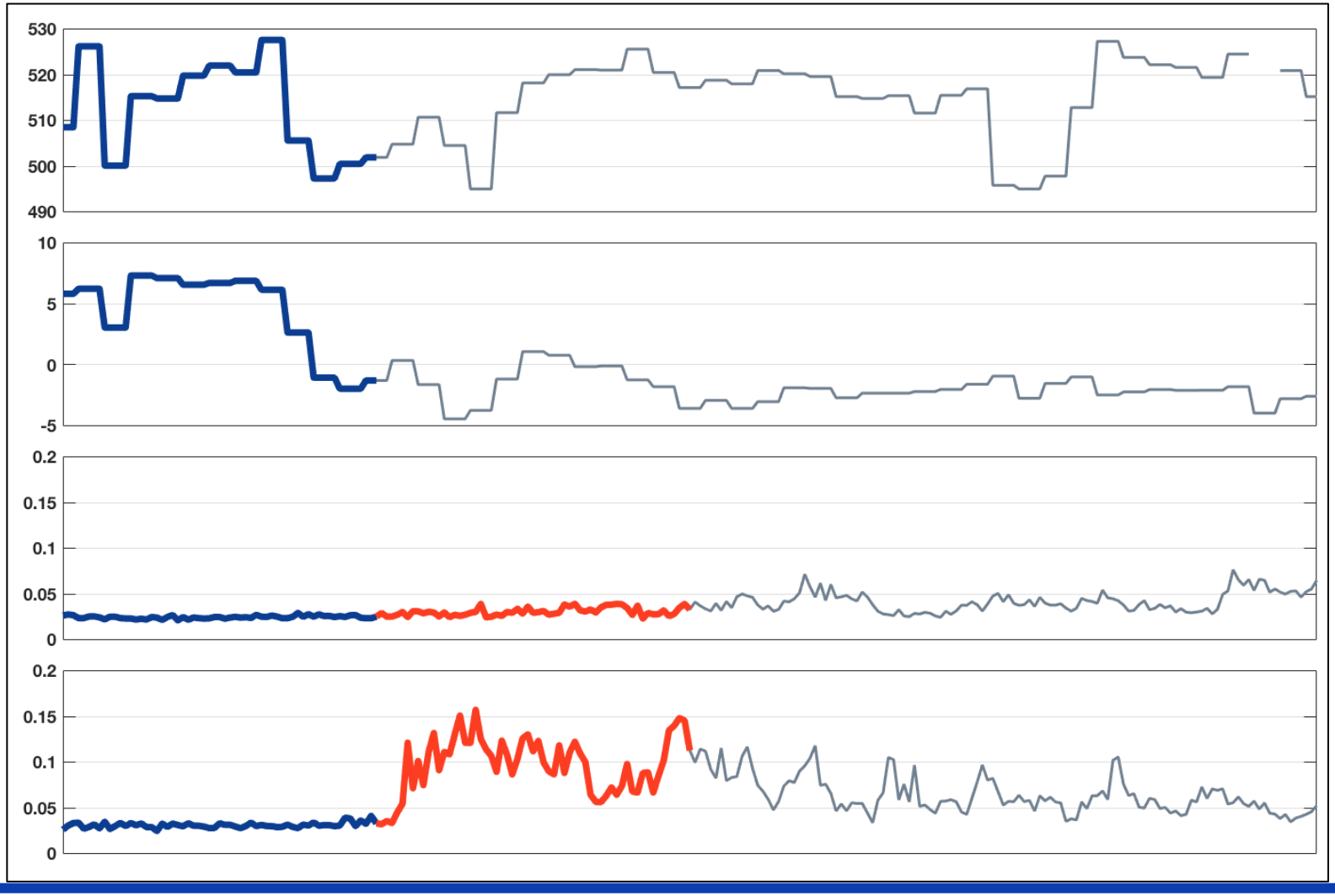
Step 2:
Define the task

Solar wind speed (km/s)

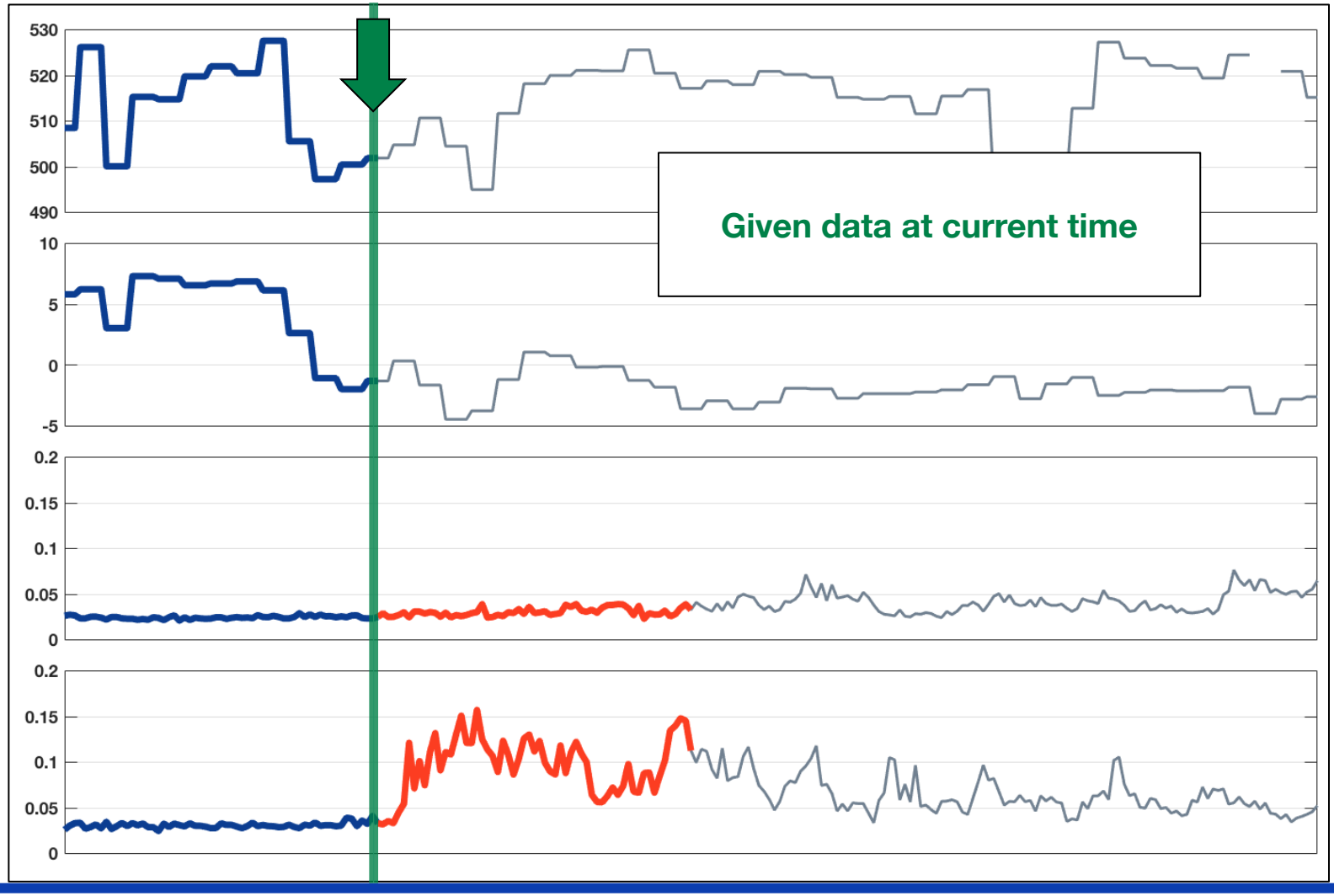
Solar wind magnetic field Z-component (nT)

Scintillation Coral Harbor station [rad]

Scintillation Gjoa Haven station [rad]

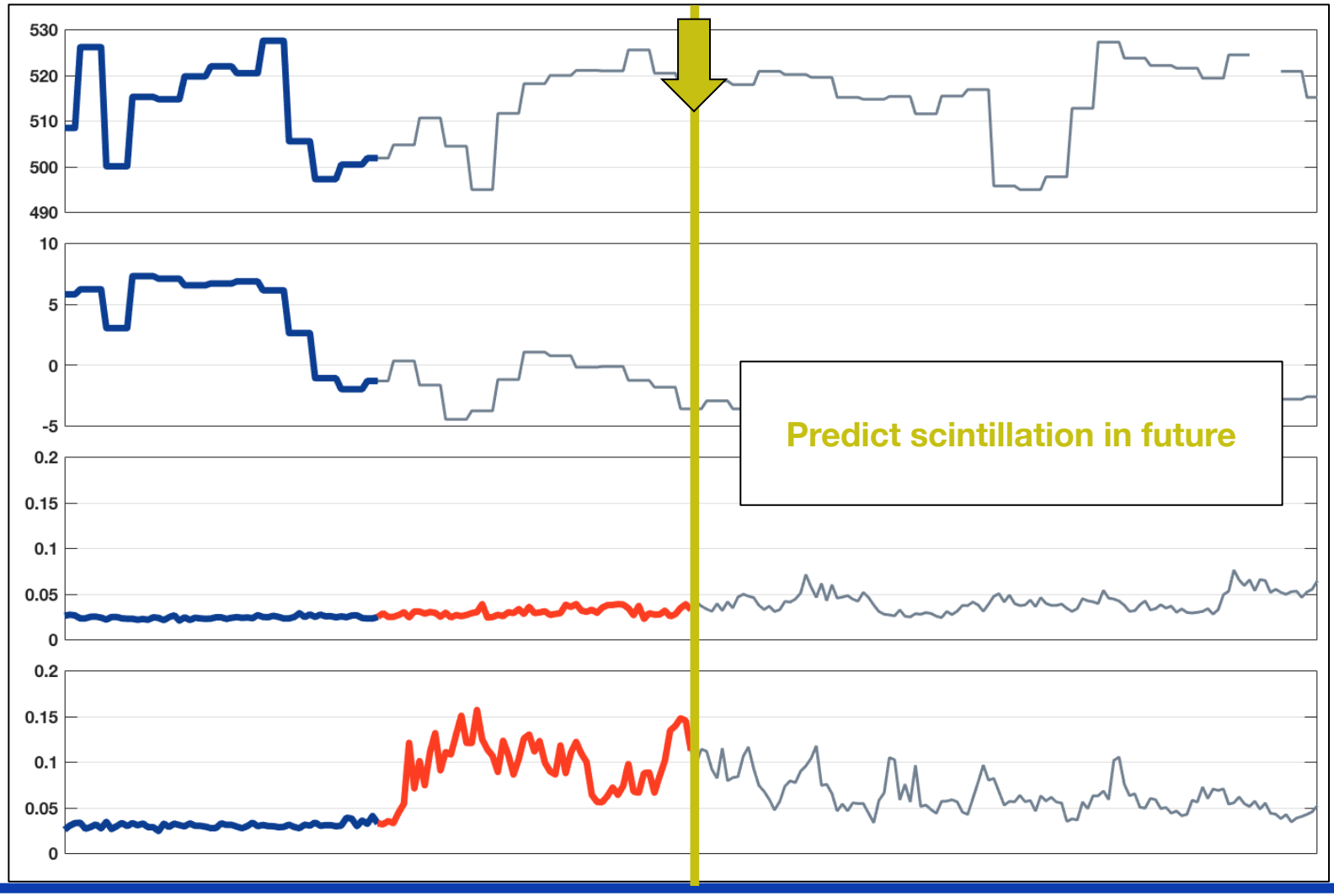


Step 2:
Define the task



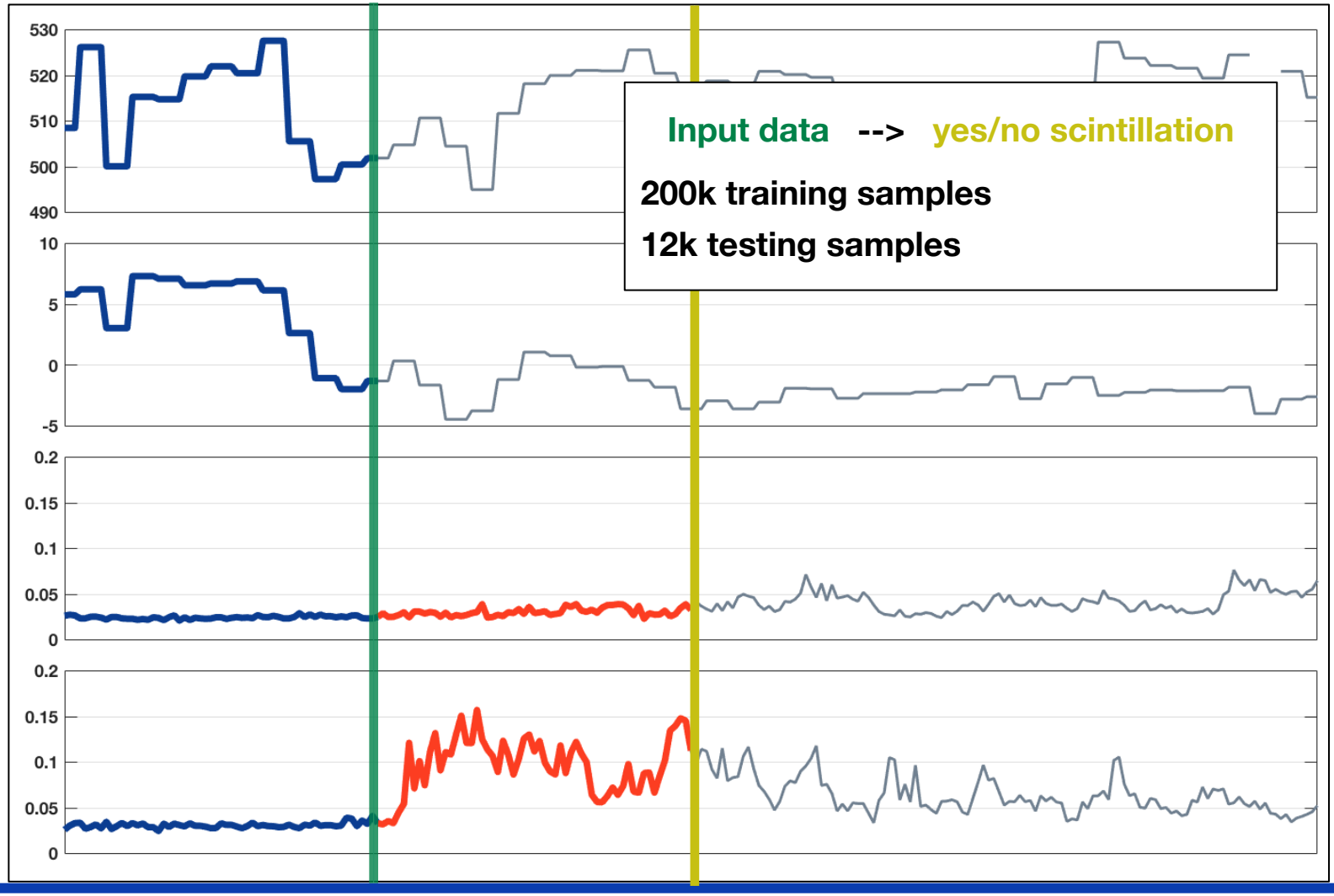
Step 2:
Define the task

Heliophysics & space weather - **Data-driven space weather** - Exciting future

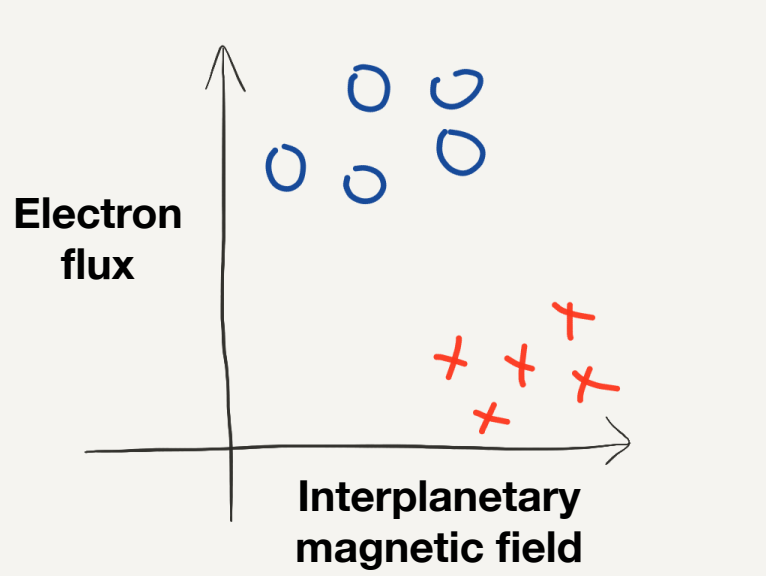


Step 2:
Define the task

Heliophysics & space weather - **Data-driven space weather** - Exciting future

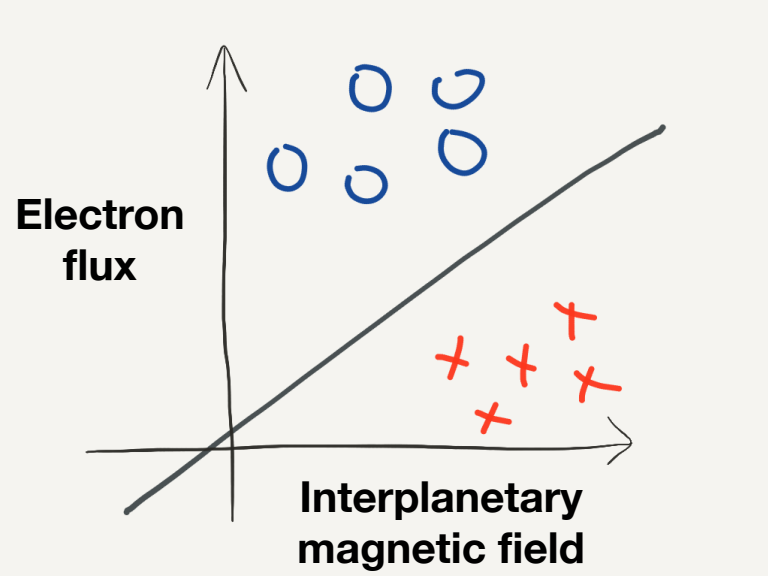


Support Vector Machine



Cortes and Vapnik (1995)

Support Vector Machine



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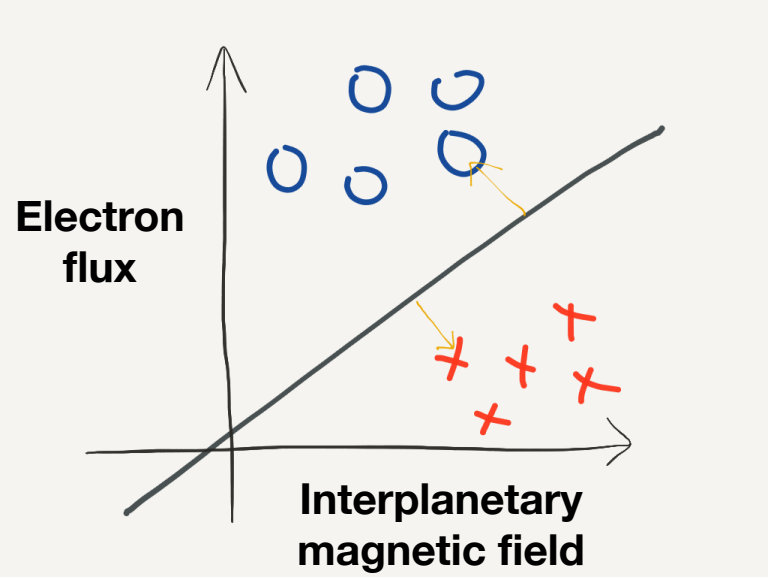
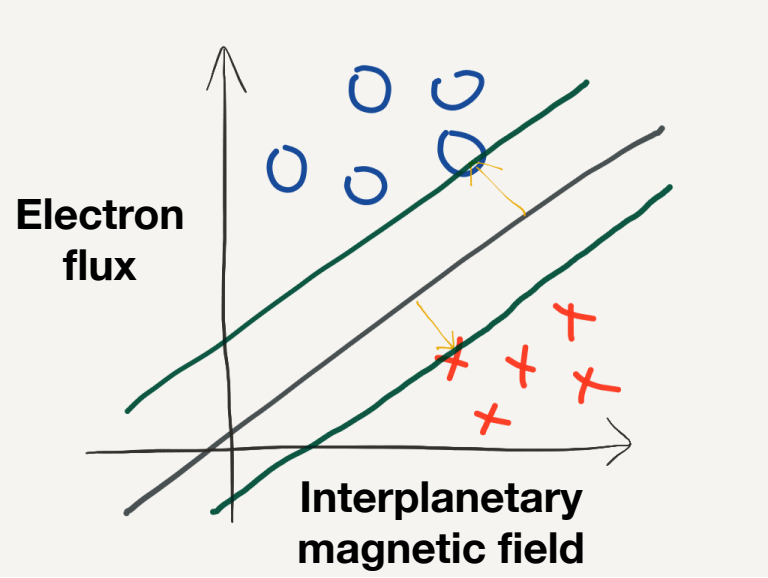
Support Vector Machine



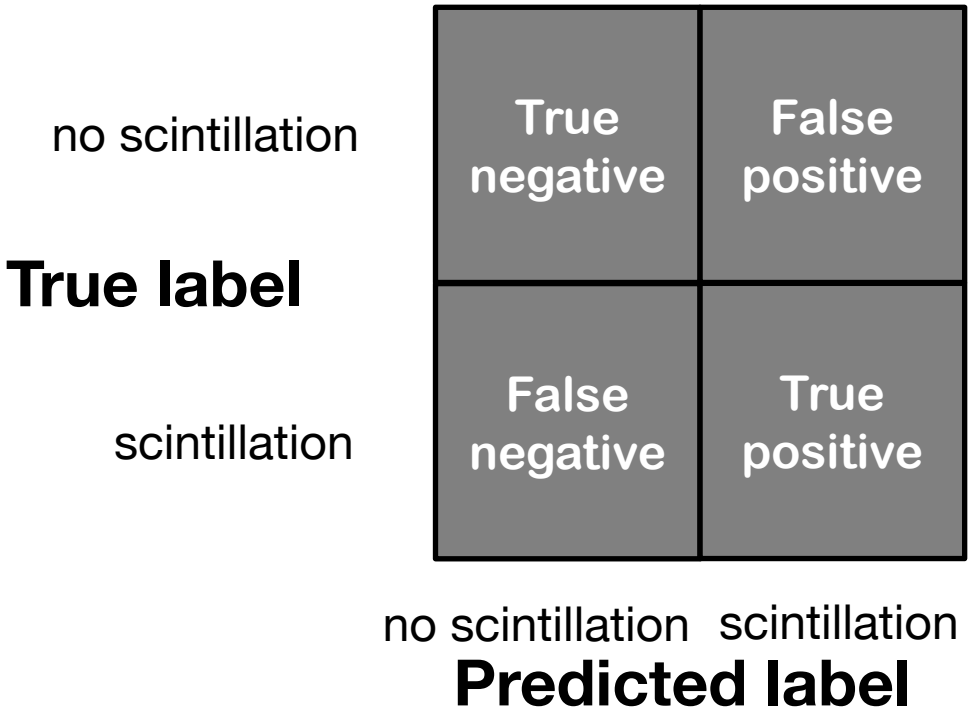
Cortes and Vapnik (1995)

Support Vector Machine



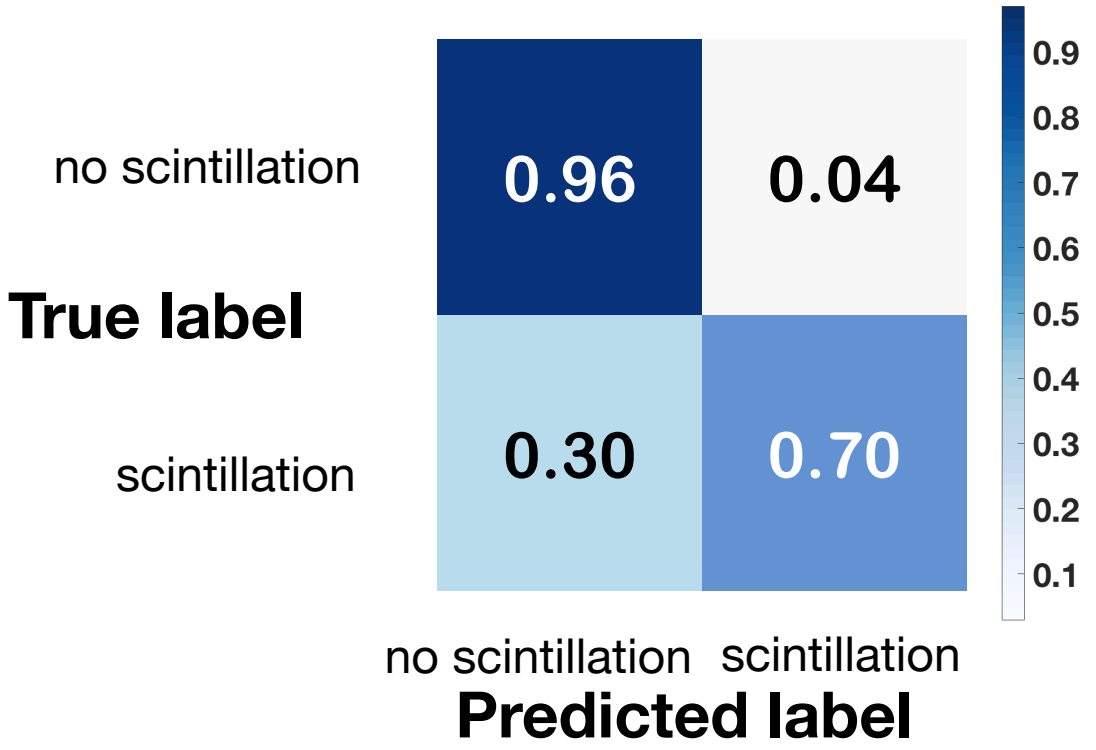
Cortes and Vapnik (1995)

Step 3:
Machine learning algorithm for prediction



McGranaghan et al., (2018) *in prep*.

Step 3:
Machine learning algorithm for prediction



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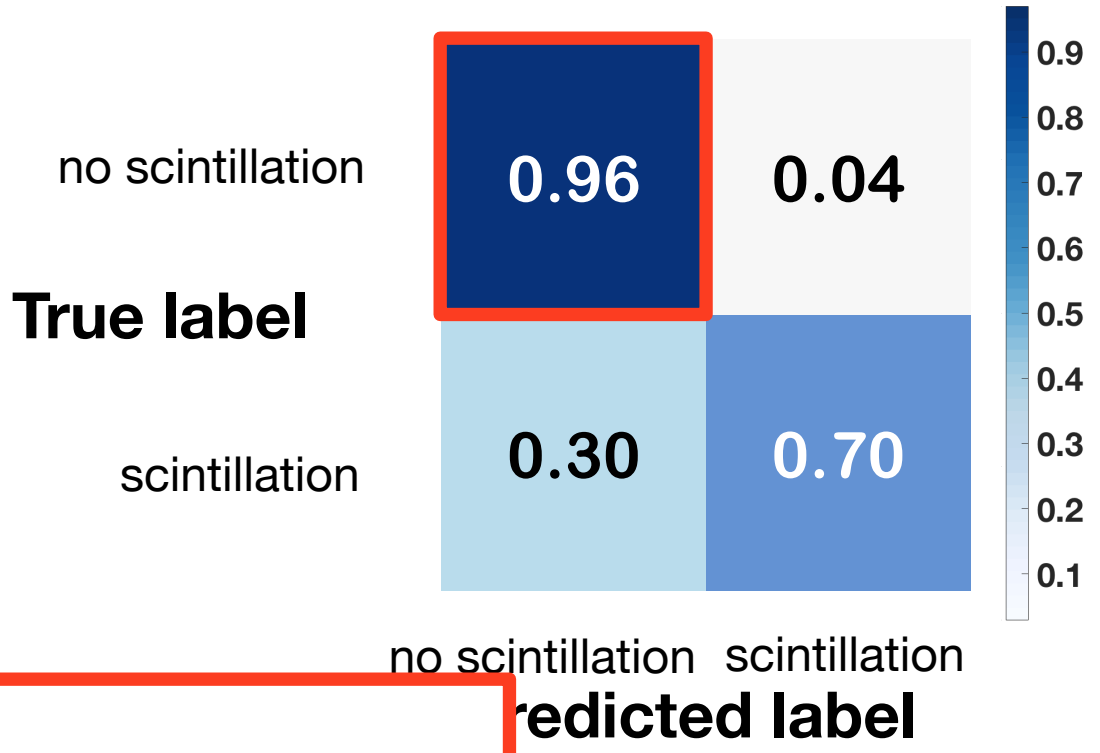


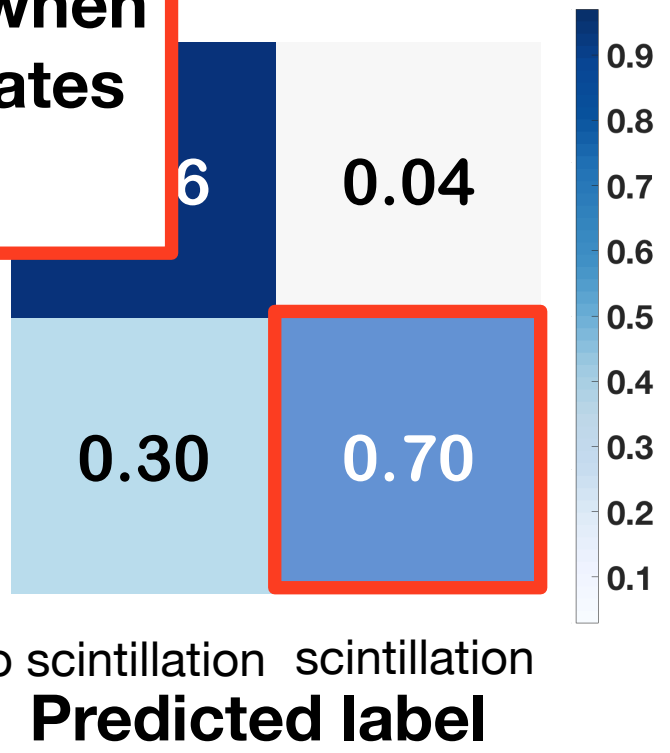
96%

High accuracy predicting when scintillation would not occur

Exciting future

70%

Improved ability to predict when scintillation will occur indicates potential of approach



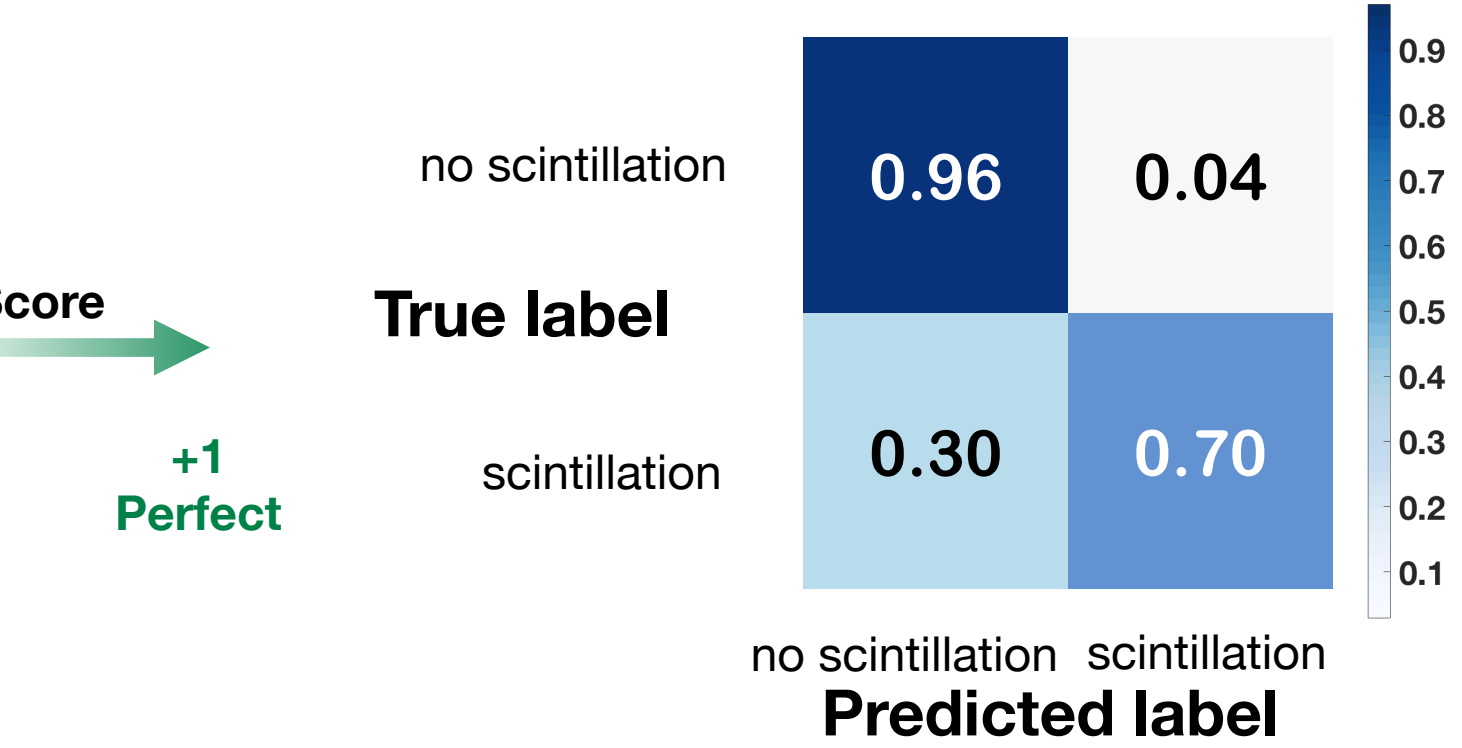
McGranaghan et al., (2018) *in prep*.

Step 3:
Machine learning algorithm for prediction

Total Skill Score

-1
Worst

+1
Perfect



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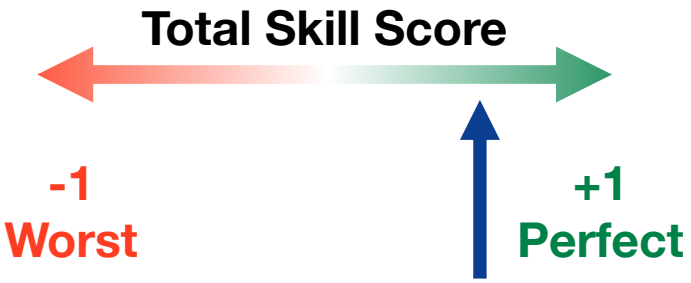

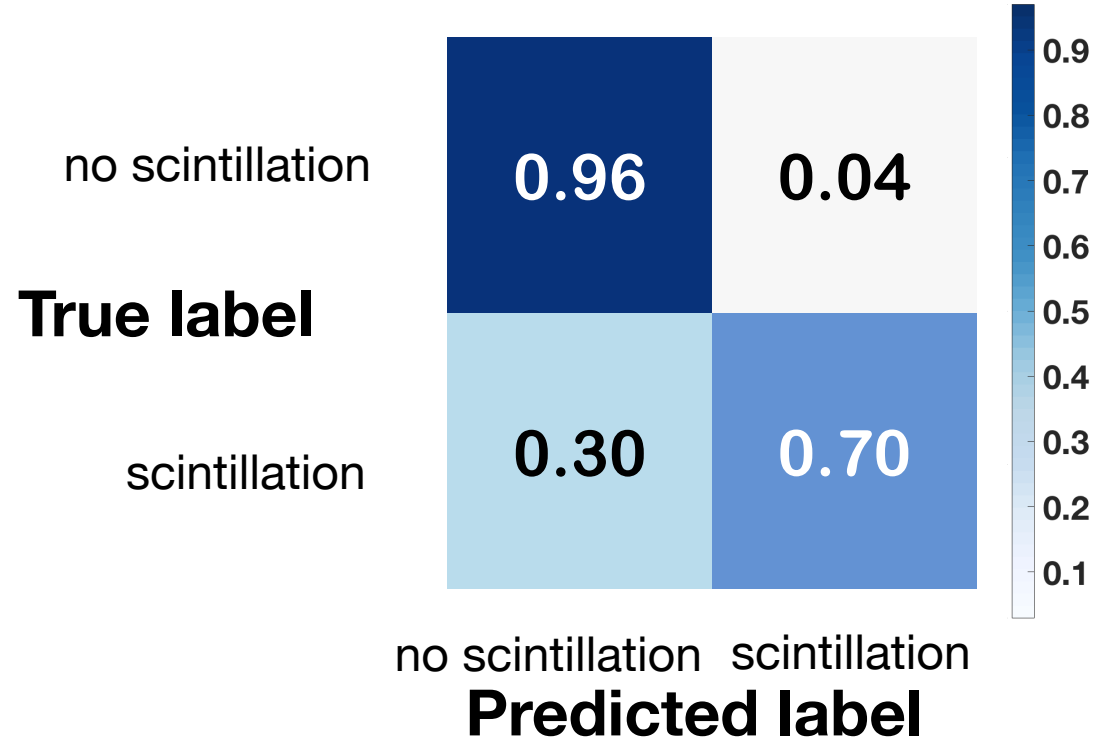

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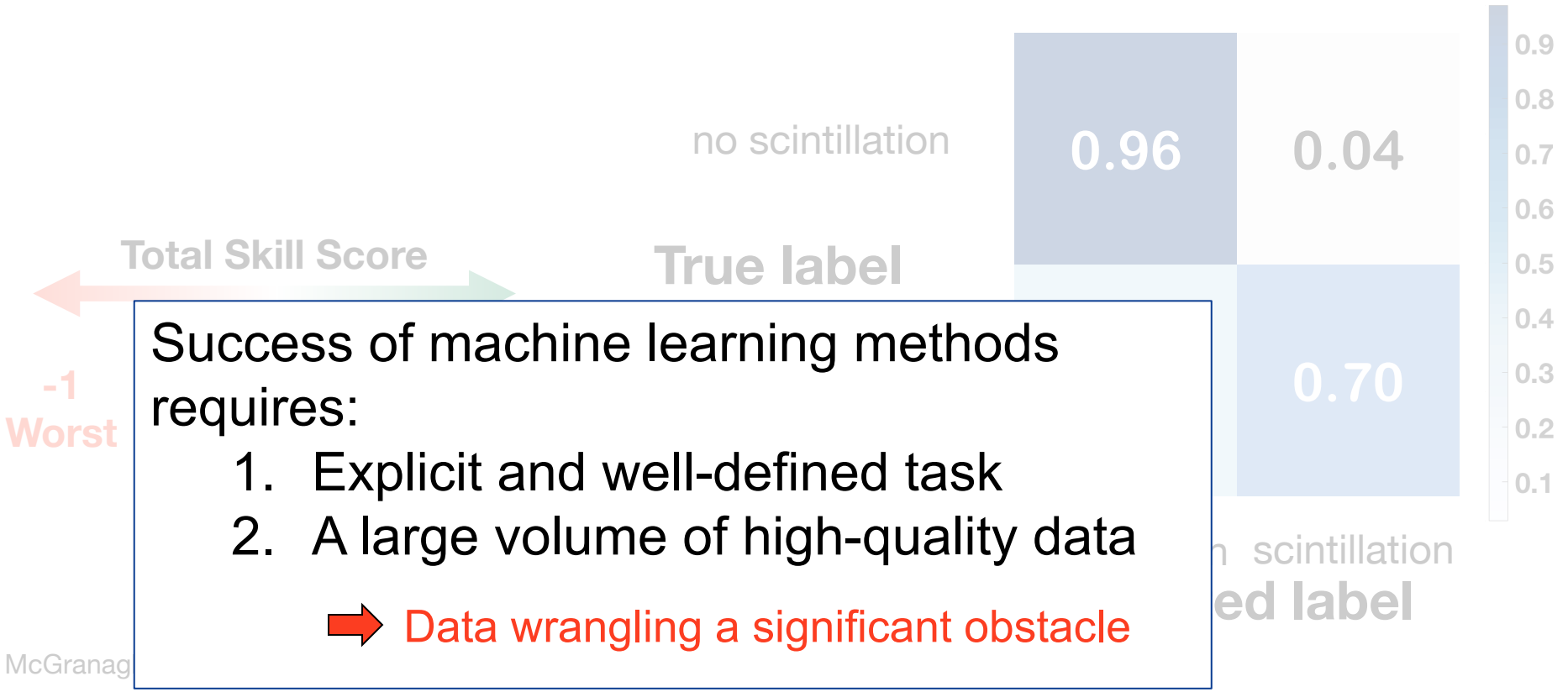

Success of machine learning methods requires:

1. Explicit and well-defined task
2. A large volume of high-quality data

➡ Data wrangling a significant obstacle

STRETCHING GNSS SIGNALS FOR SPACE WEATHER DISCOVERY

JPL

Ryan McGranaghan, Anthony Mannucci
University Corporation for Atmospheric Research (UCAR)
NASA Jet Propulsion Laboratory, California Institute of Technology

Brian Wilson, Chris Mattmann, Sujen Shah, Huikyo Lee
NASA Jet Propulsion Laboratory, California Institute of Technology

What is the impact across JPL?

Image credit: *NASA, technology drives exploration*

The importance of WEATHER IN SPACE and how data science will help us understand it

@AeroSciengineer
ryan.mcgranaghan@jpl.nasa.gov

What is space weather?

Variations in space environment
Increasingly important to our technological society

The importance of WEATHER IN SPACE and how data science will help us understand it

@AeroSciengineer
ryan.mcgranaghan@jpl.nasa.gov

What is space weather?

What if space weather were an exploration, data-driven science?

Innovative new methods lead to improved understanding and prediction

The importance of WEATHER IN SPACE and how data science will help us understand it

@AeroSciengineer
ryan.mcgranaghan@jpl.nasa.gov

What is space weather?

What if space weather were an exploration, data-driven science?

What is the impact across JPL?

Space weather applications promote interdisciplinary work and cross-cutting capabilities

Backup slides

USHERING IN A NEW FRONTIER IN SPACE SCIENCE

Ryan McGranaghan
University Corporation for Atmospheric Research (UCAR)
NASA Jet Propulsion Laboratory, California Institute of Technology

Tony Mannucci, Olga Verkhoglyadova, Nishant Malik
NASA JPL, Dartmouth College

USHERING IN A NEW FRONTIER IN SPACE SCIENCE

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NASA JPL, Dartmouth College

1. What is space weather?
2. What if space weather were an exploration, data-driven science?
3. What does this mean to the future of JPL? (*change how we work, cross-cutting work, new exploration*)

The importance of WEATHER IN SPACE and how data science will help us understand it

Ryan McGranaghan

University Corporation for Atmospheric Research (UCAR)
NASA Jet Propulsion Laboratory, California Institute of Technology

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NASA JPL, Dartmouth College

1. What is space weather?
2. What if space weather were an exploration, data-driven science?
3. What is the impact across JPL?

ace weather, data

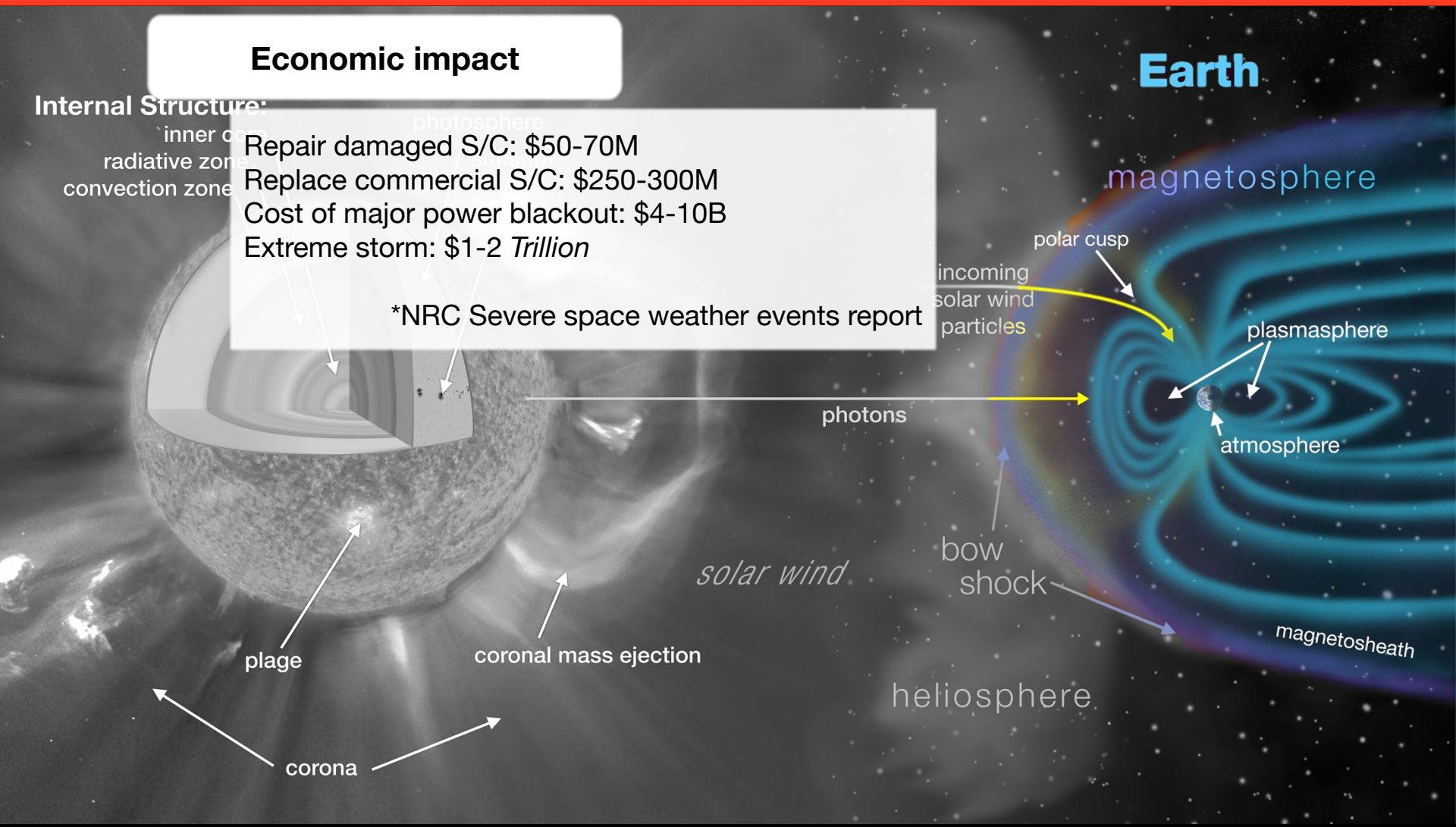
What is space weather?

Heliophysics & space weather - Data-driven space weather - Exciting future

Economic impact

Repair damaged S/C: $50-70M
Replace commercial S/C: $250-300M
Cost of major power blackout: $4-10B
Extreme storm: $1-2 *Trillion*

*NRC Severe space weather events report



What is space weather?

- Data-driven space weather - Exciting future

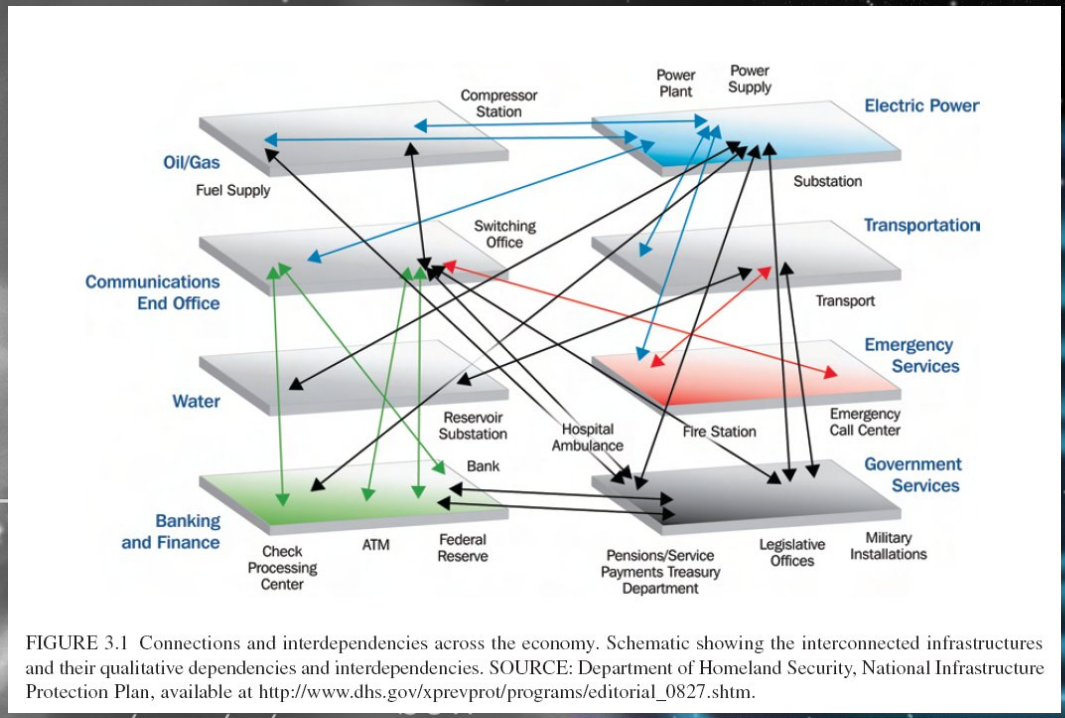


FIGURE 3.1 Connections and interdependencies across the economy. Schematic showing the interconnected infrastructures and their qualitative dependencies and interdependencies. SOURCE: Department of Homeland Security, National Infrastructure Protection Plan, available at http://www.dhs.gov/xprevprot/programs/editorial_0827.shtm.

solar wind

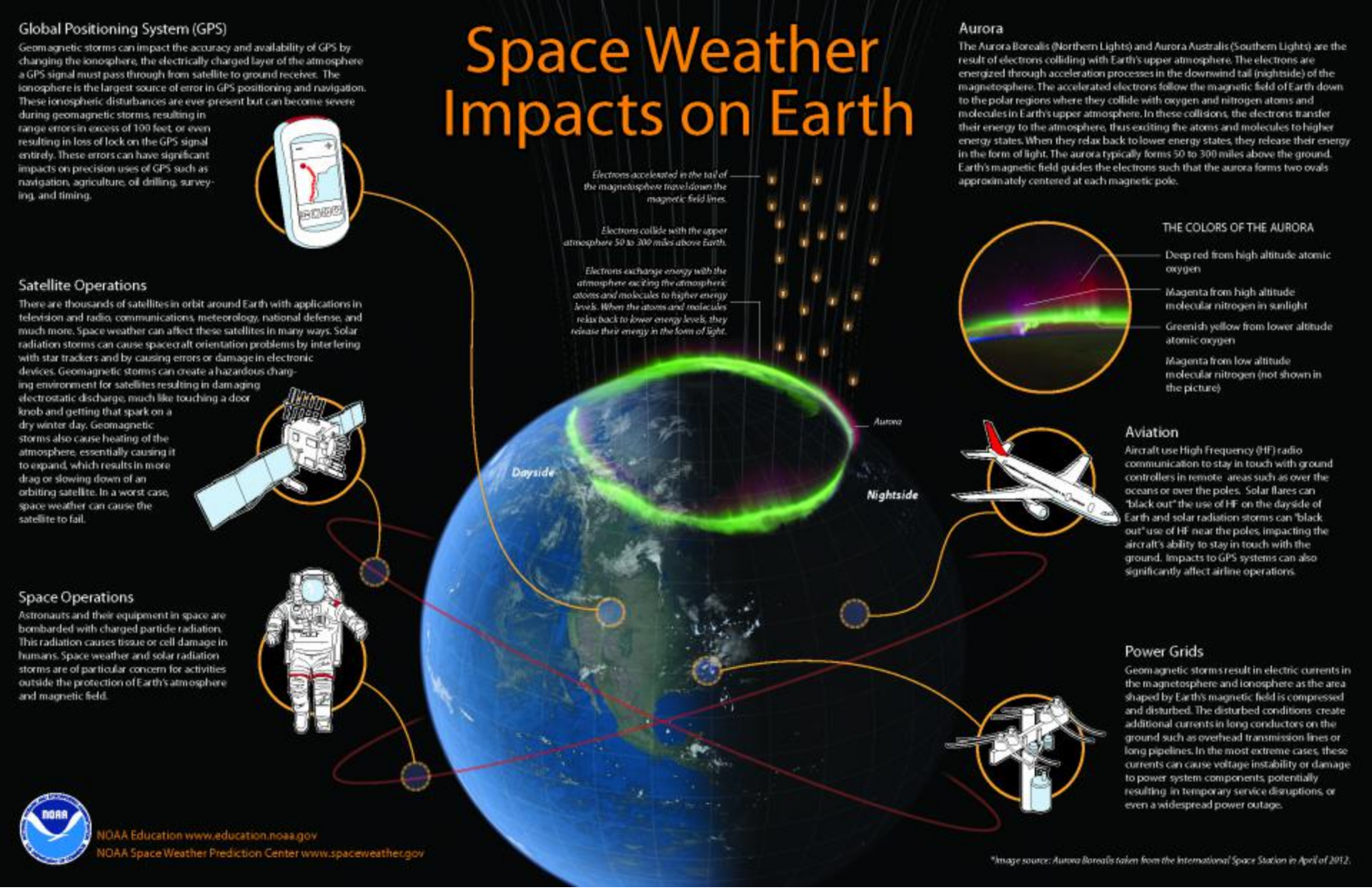
shock

magnetosheath

ejection

heliosphere

corona


Space Weather Impacts on Earth
Global Positioning System (GPS)
Geomagnetic storms can impact the accuracy and availability of GPS by changing the ionosphere, the electrically charged layer of the atmosphere a GPS signal must pass through from satellite to ground receiver. The ionosphere is the largest source of error in GPS positioning and navigation. These ionospheric disturbances are ever-present but can become severe during geomagnetic storms, resulting in range errors in excess of 100 feet, or even resulting in loss of lock on the GPS signal entirely. These errors can have significant impacts on precision uses of GPS such as navigation, agriculture, oil drilling, surveying, and timing.
Satellite Operations
There are thousands of satellites in orbit around Earth with applications in television and radio, communications, meteorology, national defense, and much more. Space weather can affect these satellites in many ways. Solar radiation storms can cause spacecraft orientation problems by interfering with star trackers and by causing errors or damage in electronic devices. Geomagnetic storms can create a hazardous charging environment for satellites resulting in damaging electrostatic discharge, much like touching a door knob and getting that spark on a dry winter day. Geomagnetic storms also cause heating of the atmosphere, essentially causing it to expand, which results in more drag or slowing down of an orbiting satellite. In a worst case, space weather can cause the satellite to fail.
Space Operations
Astronauts and their equipment in space are bombarded with charged particle radiation. This radiation causes tissue or cell damage in humans. Space weather and solar radiation storms are of particular concern for activities outside the protection of Earth's atmosphere and magnetic field.
Electrons accelerated in the tail of the magnetosphere travel down the magnetic field lines.
Electrons collide with the upper atmosphere 50 to 300 miles above Earth.
Electrons exchange energy with the atmosphere exciting the atmospheric atoms and molecules to higher energy levels. When the atoms and molecules relax back to lower energy levels, they release their energy in the form of light.
Aurora
Dayside
Nightside
Aurora
The Aurora Borealis (Northern Lights) and Aurora Australis (Southern Lights) are the result of electrons colliding with Earth's upper atmosphere. The electrons are energized through acceleration processes in the downwind tail (nightside) of the magnetosphere. The accelerated electrons follow the magnetic field of Earth down to the polar regions where they collide with oxygen and nitrogen atoms and molecules in Earth's upper atmosphere. In these collisions, the electrons transfer their energy to the atmosphere, thus exciting the atoms and molecules to higher energy states. When they relax back to lower energy states, they release their energy in the form of light. The aurora typically forms 50 to 300 miles above the ground. Earth's magnetic field guides the electrons such that the aurora forms two ovals approximately centered at each magnetic pole.
THE COLORS OF THE AURORA
Deep red from high altitude atomic oxygen
Magenta from high altitude molecular nitrogen in sunlight
Greenish yellow from lower altitude atomic oxygen
Magenta from low altitude molecular nitrogen (not shown in the picture)
Aviation
Aircraft use High Frequency (HF) radio communication to stay in touch with ground controllers in remote areas such as over the oceans or over the poles. Solar flares can "black out" the use of HF on the dayside of Earth and solar radiation storms can "black out" use of HF near the poles, impacting the aircraft's ability to stay in touch with the ground. Impacts to GPS systems can also significantly affect airline operations.
Power Grids
Geomagnetic storms result in electric currents in the magnetosphere and ionosphere as the area shaped by Earth's magnetic field is compressed and disturbed. The disturbed conditions create additional currents in long conductors on the ground such as overhead transmission lines or long pipelines. In the most extreme cases, these currents can cause voltage instability or damage to power system components, potentially resulting in temporary service disruptions, or even a widespread power outage.
NOAA Education www.education.noaa.gov
NOAA Space Weather Prediction Center www.spaceweather.gov
*Image source: Aurora Borealis taken from the International Space Station in April of 2012.

HP & Sp Wx introduction

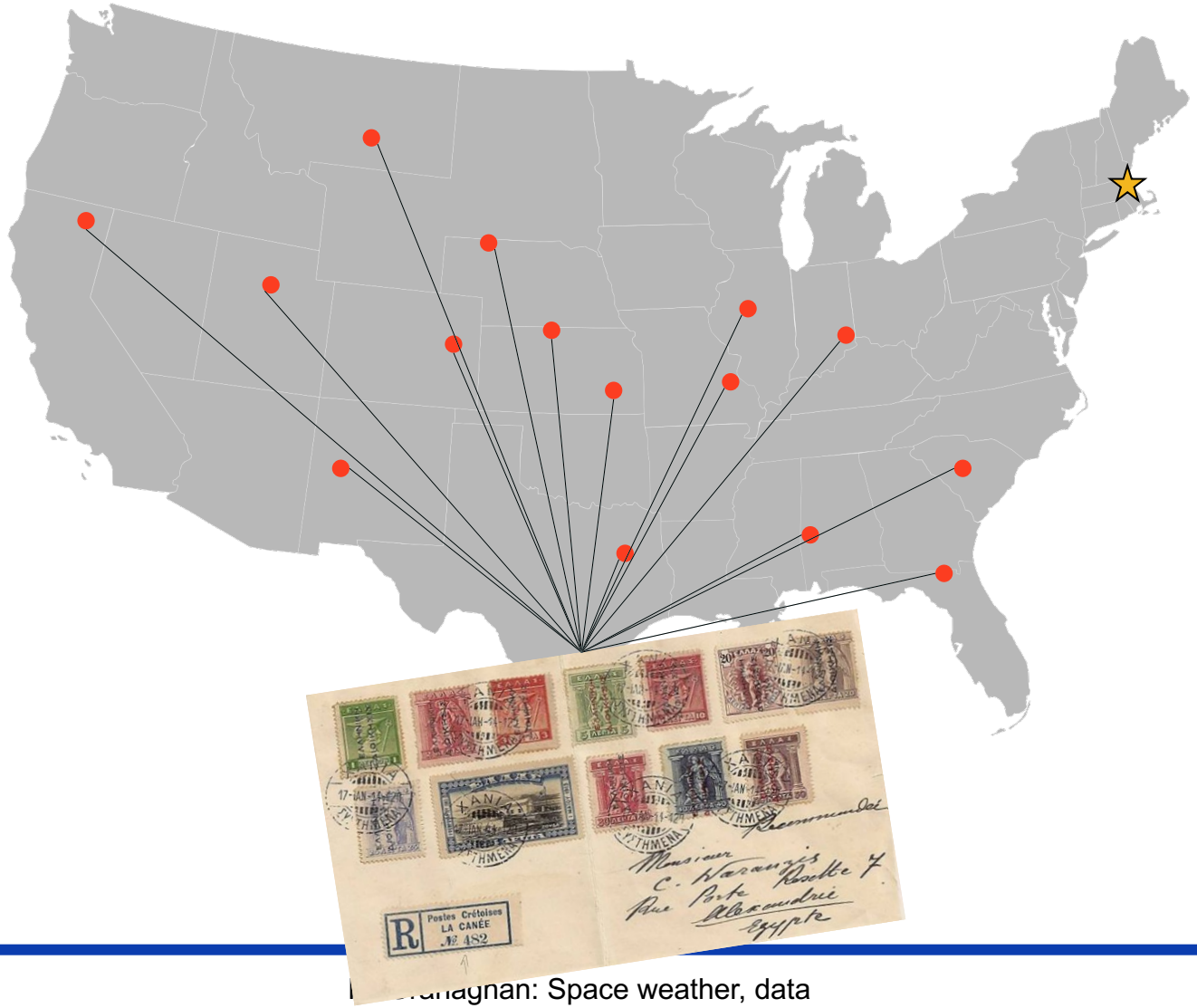
- Heliophysics is a vast and transdisciplinary subject that brings together many threads of science

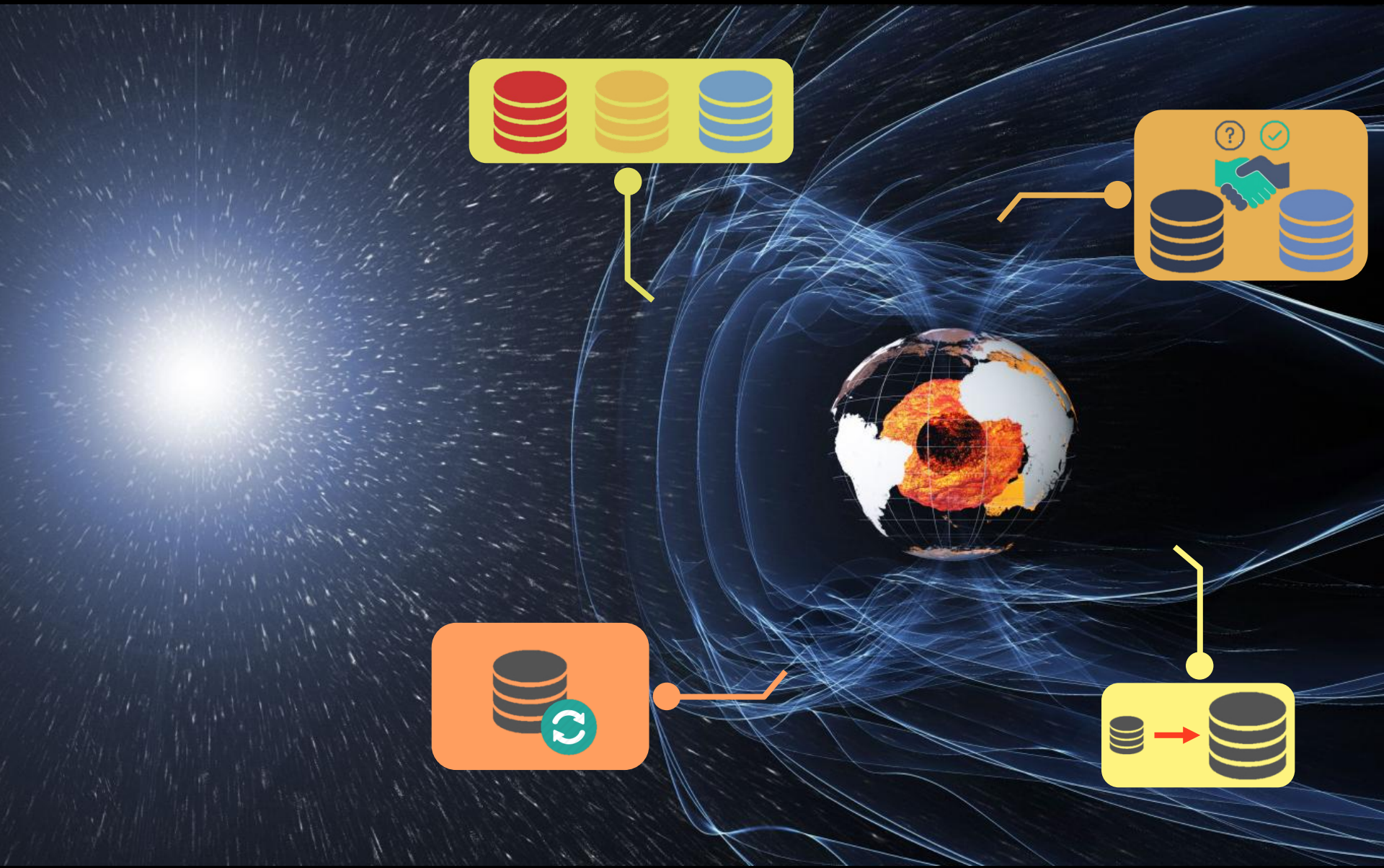
- Space weather importance to audience (*make it clear that sp. wx. affects all JPL interests*)
  - Enabling of new missions
    - ❖ Protect astronauts
    - ❖ Protect space assets
  - Enables use of space

  - New data-driven approaches will lead to rapid discovery, new capabilities, and improved understanding and ability to operate in space as well as a reduction of barriers between interdisciplinary work

Six degrees of separation and a small world

New Frontier: Network analysis - Machine learning - Exciting future

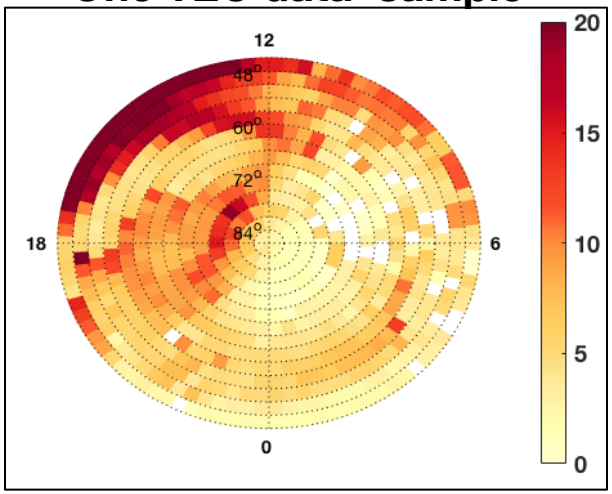





Universal challenges:
Evolve traditional approaches
Embrace data-driven discovery
Enable interdisciplinary work

TEC data
- **Converted to magnetic coordinates**
- **Accumulated over one hour**

One TEC data 'sample'



TEC data
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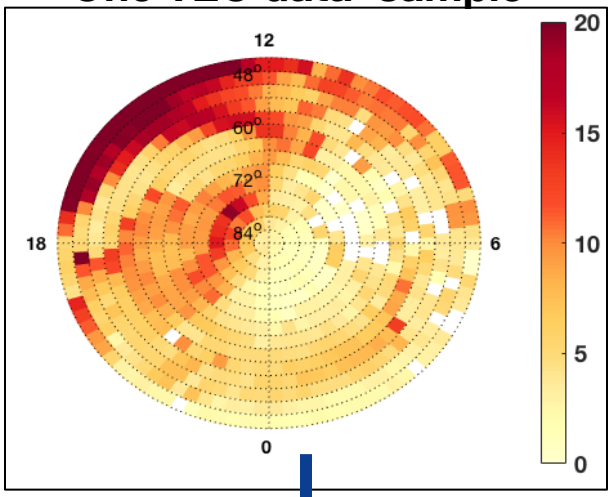
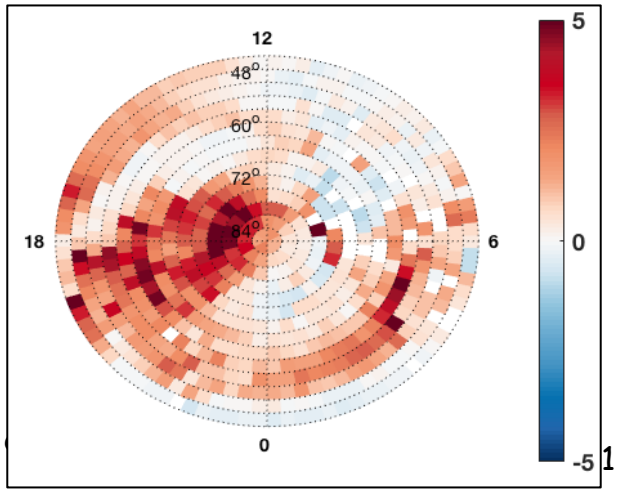
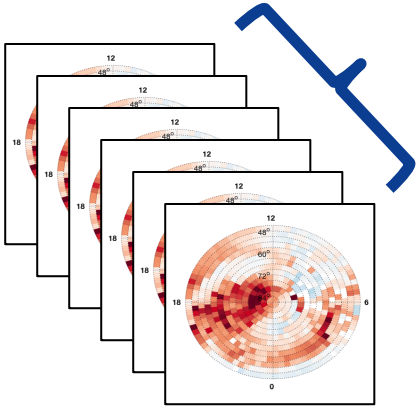
- **Accumulated over one hour**

Background level removed to identify TEC response to space weather activity

One TEC data 'sample'

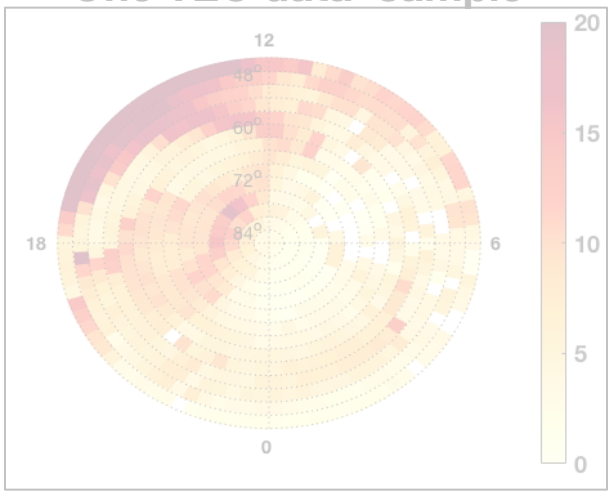


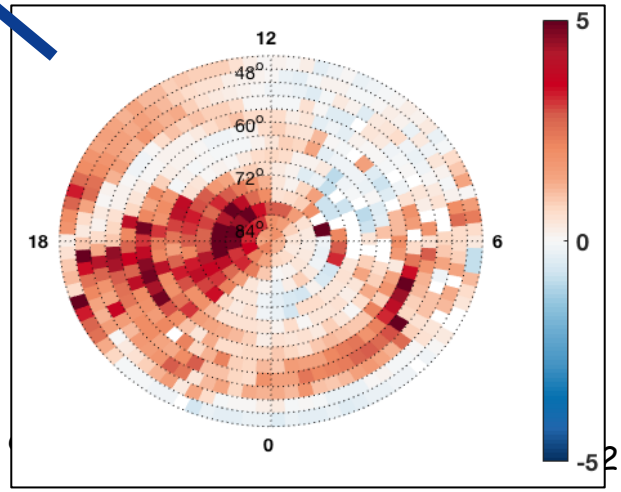


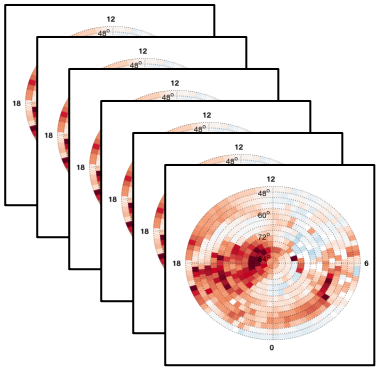


Accumulate samples over time

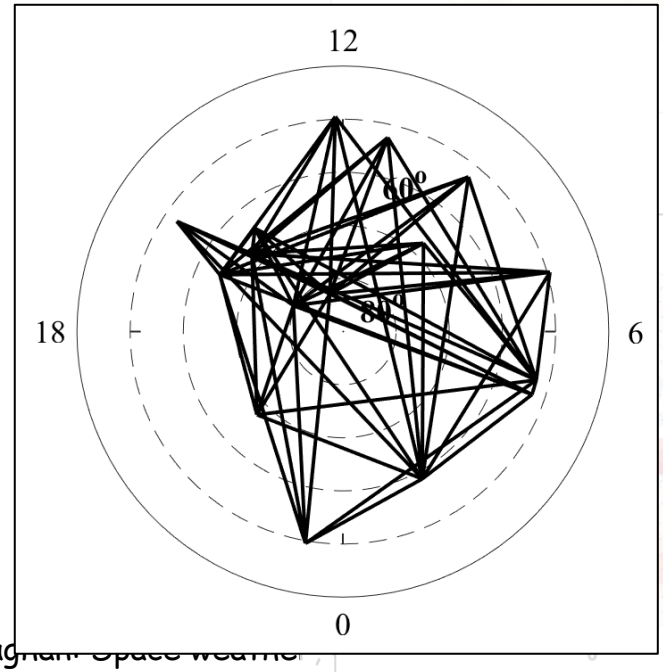
One TEC data 'sample'





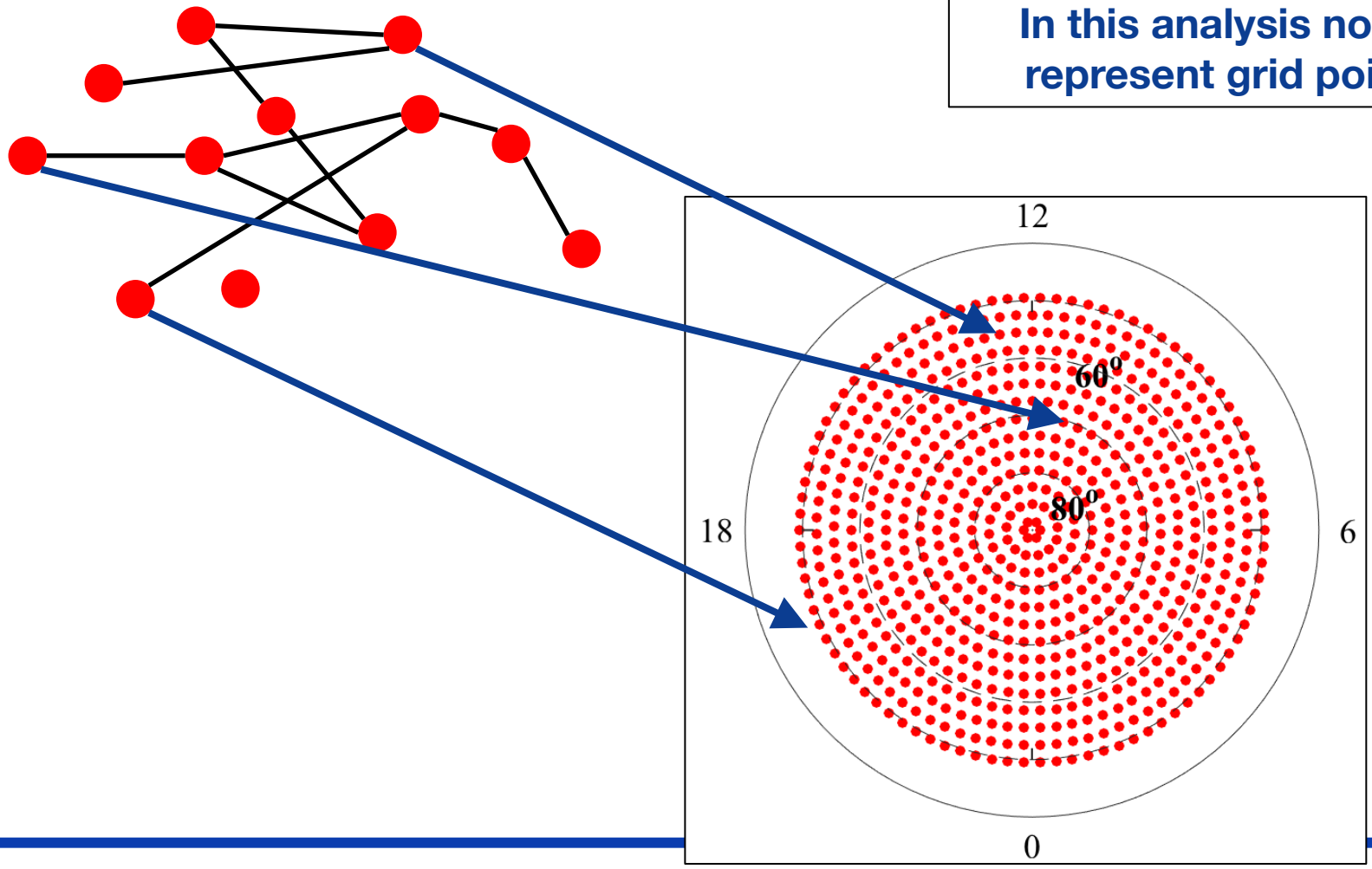


Visualize the connections



What is network analysis?

New Frontier: Network analysis - Multi-scale - Exciting future



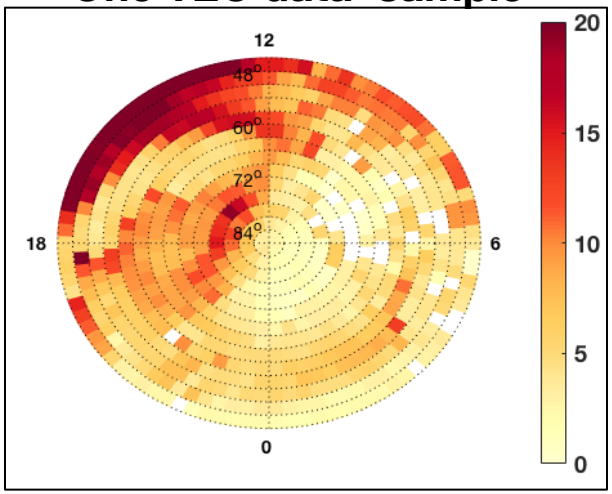
In this analysis nodes represent grid points

TEC Network analysis:
Steps

New Frontier: Network analysis - Multi-scale - Exciting future

TEC data
- **Converted to magnetic coordinates**
- **Accumulated over one hour**

One TEC data 'sample'



TEC Network analysis:
Steps

New Frontier: Network analysis - Multi-scale - Exciting future

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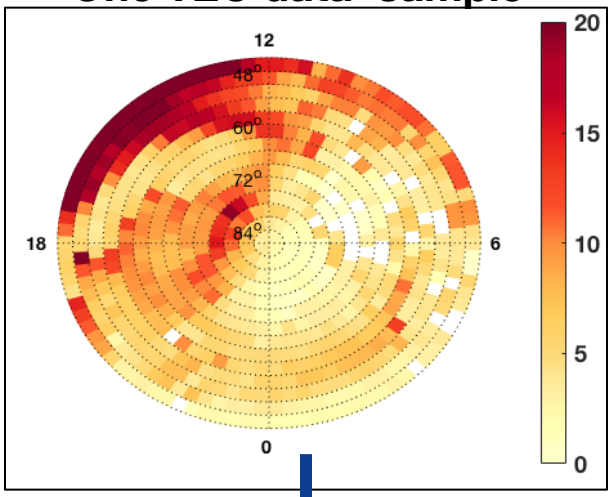
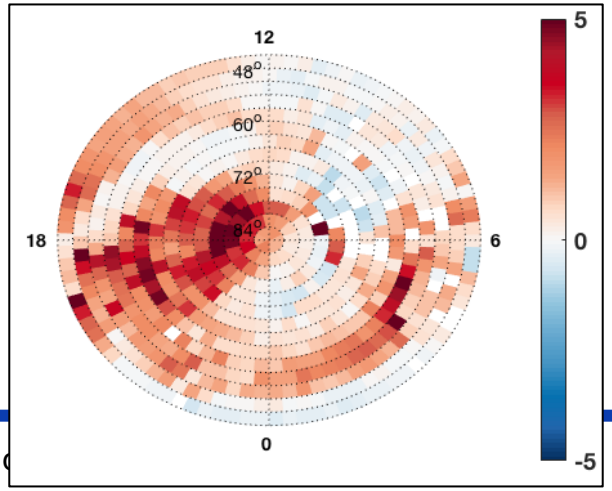
One TEC data 'sample'

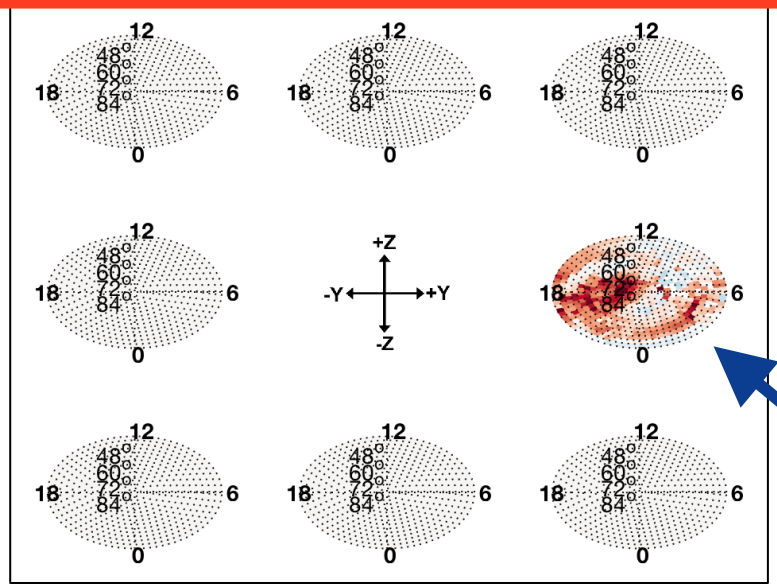


Background level removed to identify TEC response to geospace activity

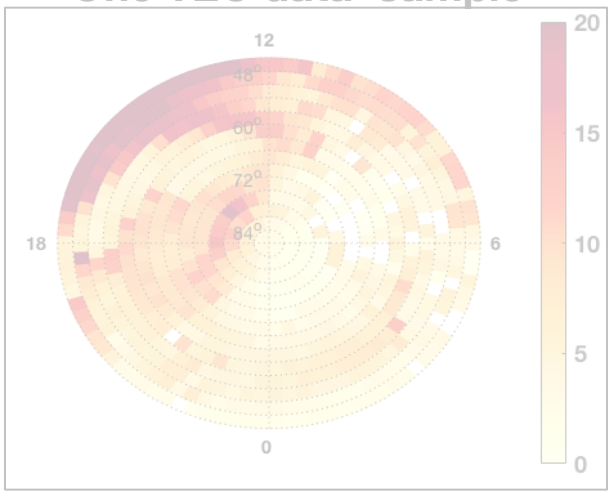


TEC Network analysis:
Steps

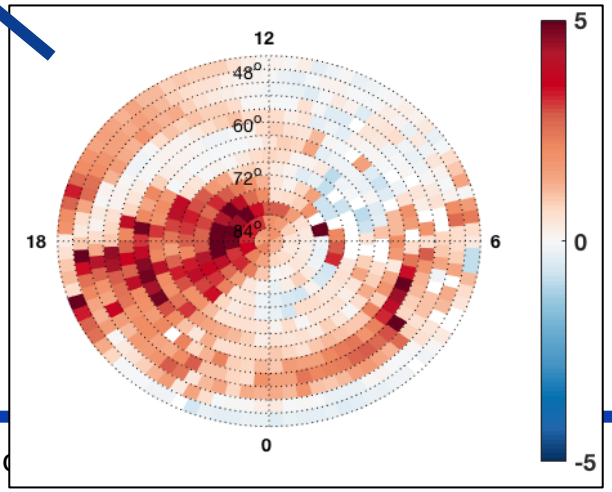
New Frontier: Network analysis - Multi-scale - Exciting future



One TEC data 'sample'

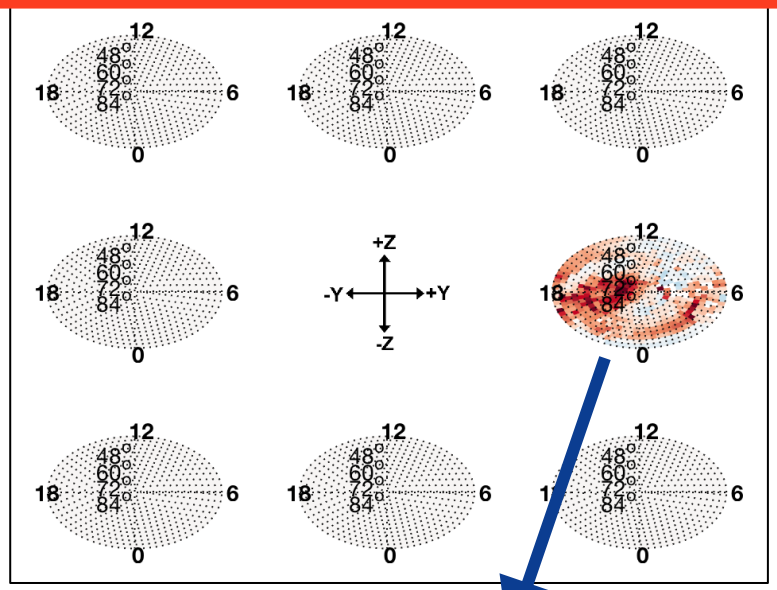


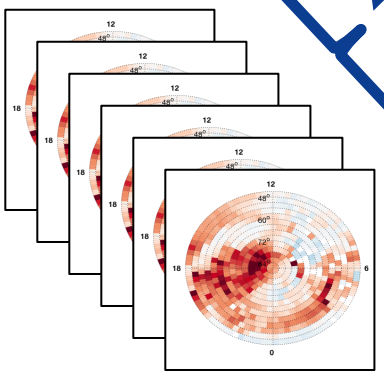
Each sample binned by IMF clock angle



TEC Network analysis:
Steps

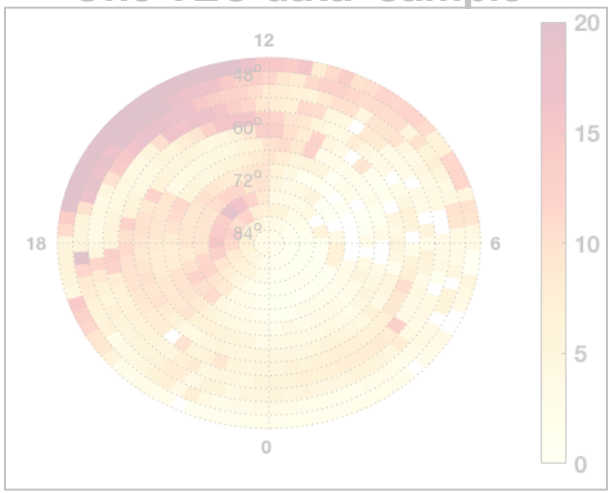
New Frontier: Network analysis - Multi-scale - Exciting future

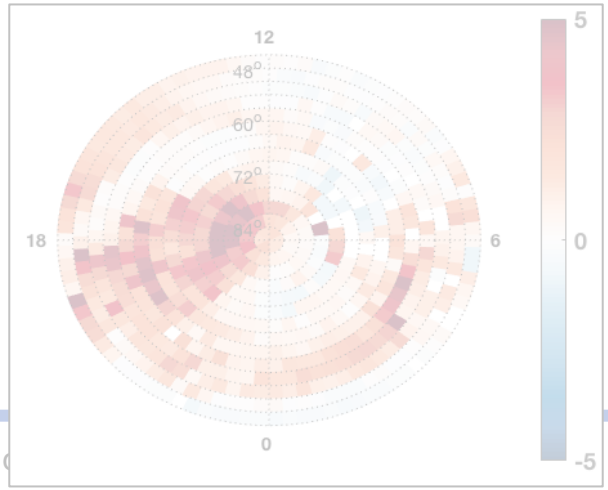




Accumulate samples over time

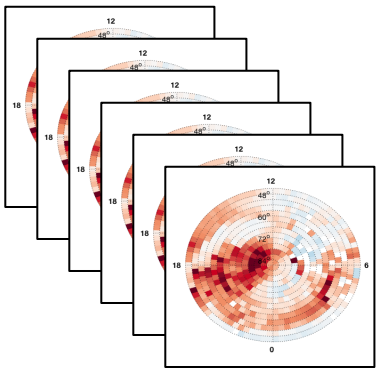
One TEC data 'sample'





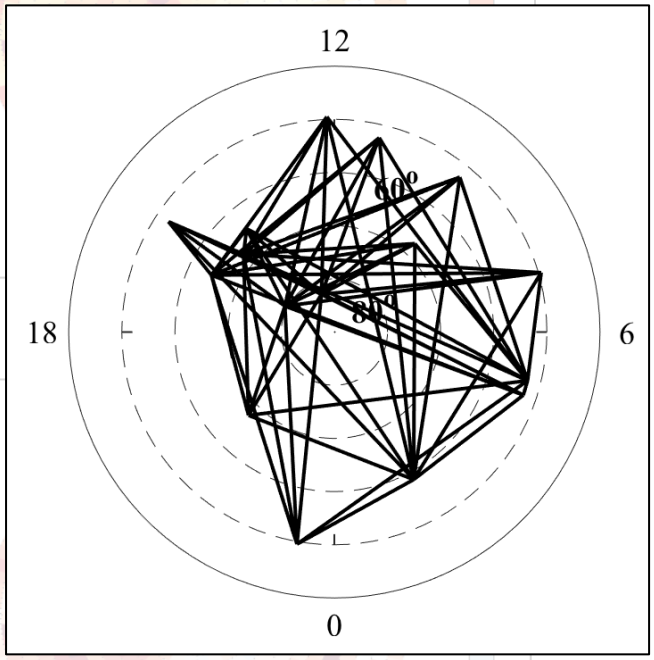
TEC Network analysis:
Steps

New Frontier: Network analysis - Multi-scale - Exciting future



Visualize the connections

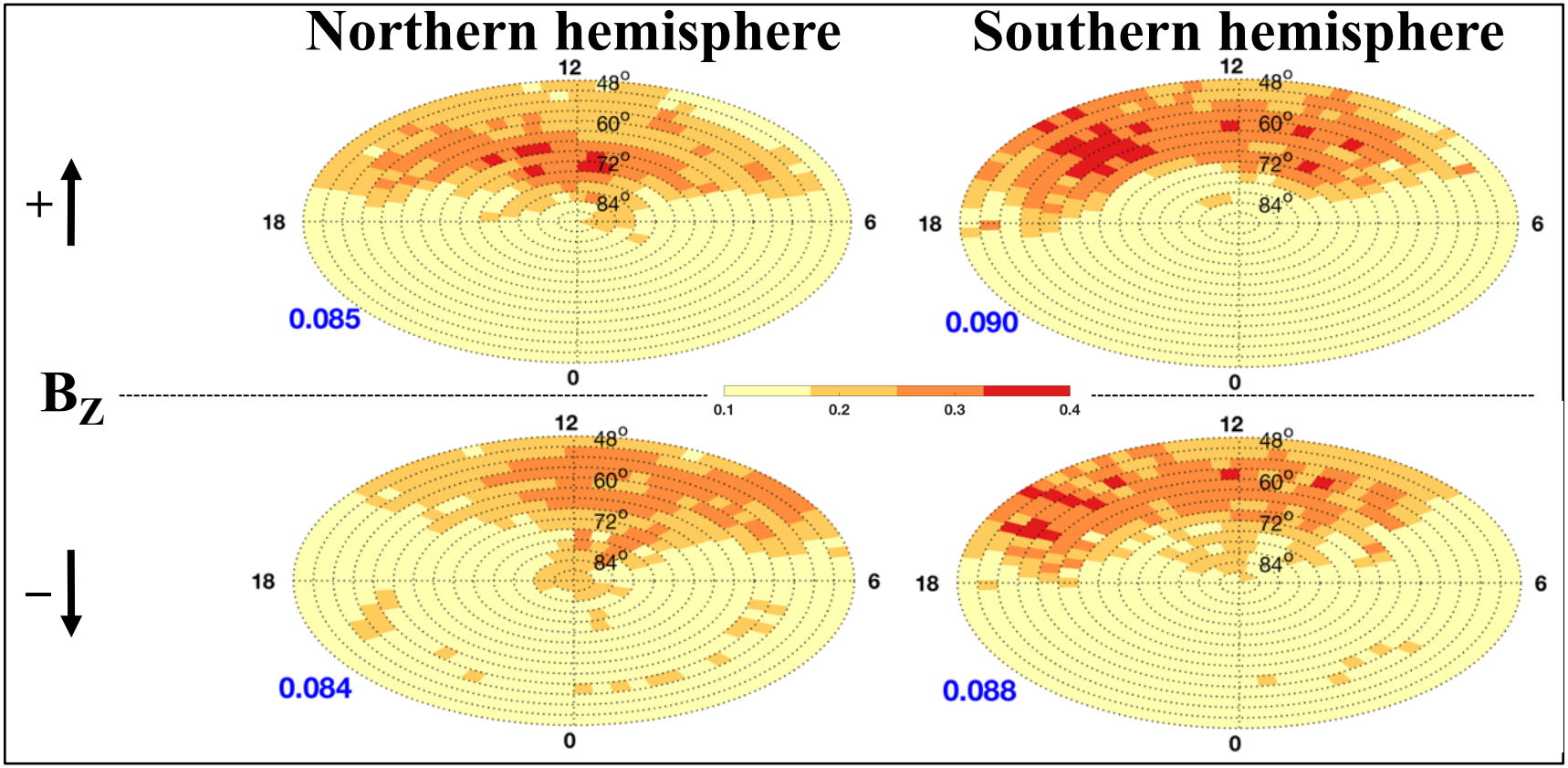
One TEC data 'sample'



Network analysis

Degree Centrality

New Frontier: Network analysis - Multi-scale - Exciting future

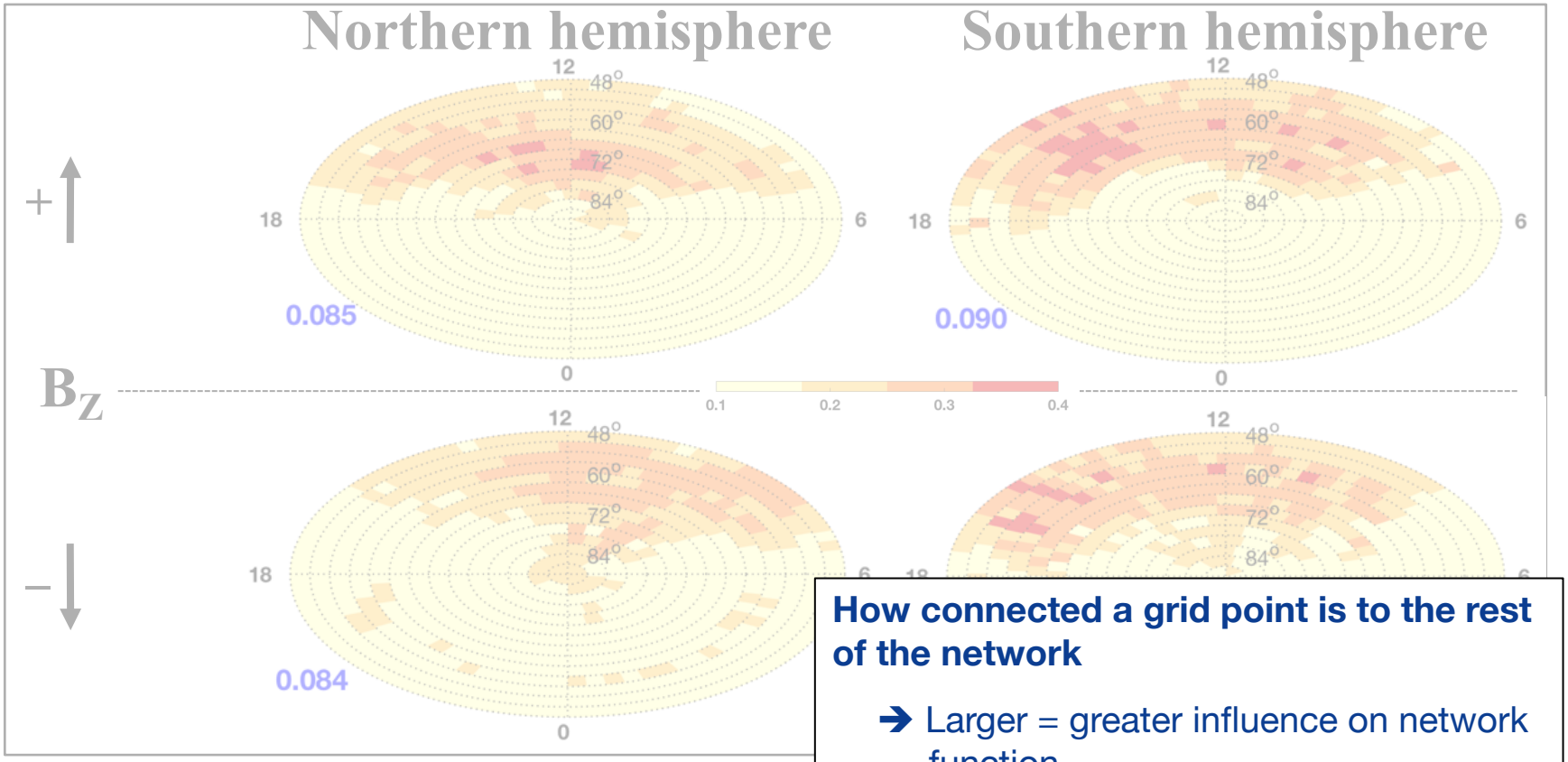


McGranaghan, R. M., A. J. Mannucci, O. Verkhoglyadova, and N. Malik (2017), Finding multiscale connectivity in our geospace observational system: Network analysis of total electron content, J. Geophys. Res. Space Physics, 122, doi:10.1002/2017JA024202.

Network analysis

Degree Centrality

New Frontier: Network analysis - Multi-scale - Exciting future



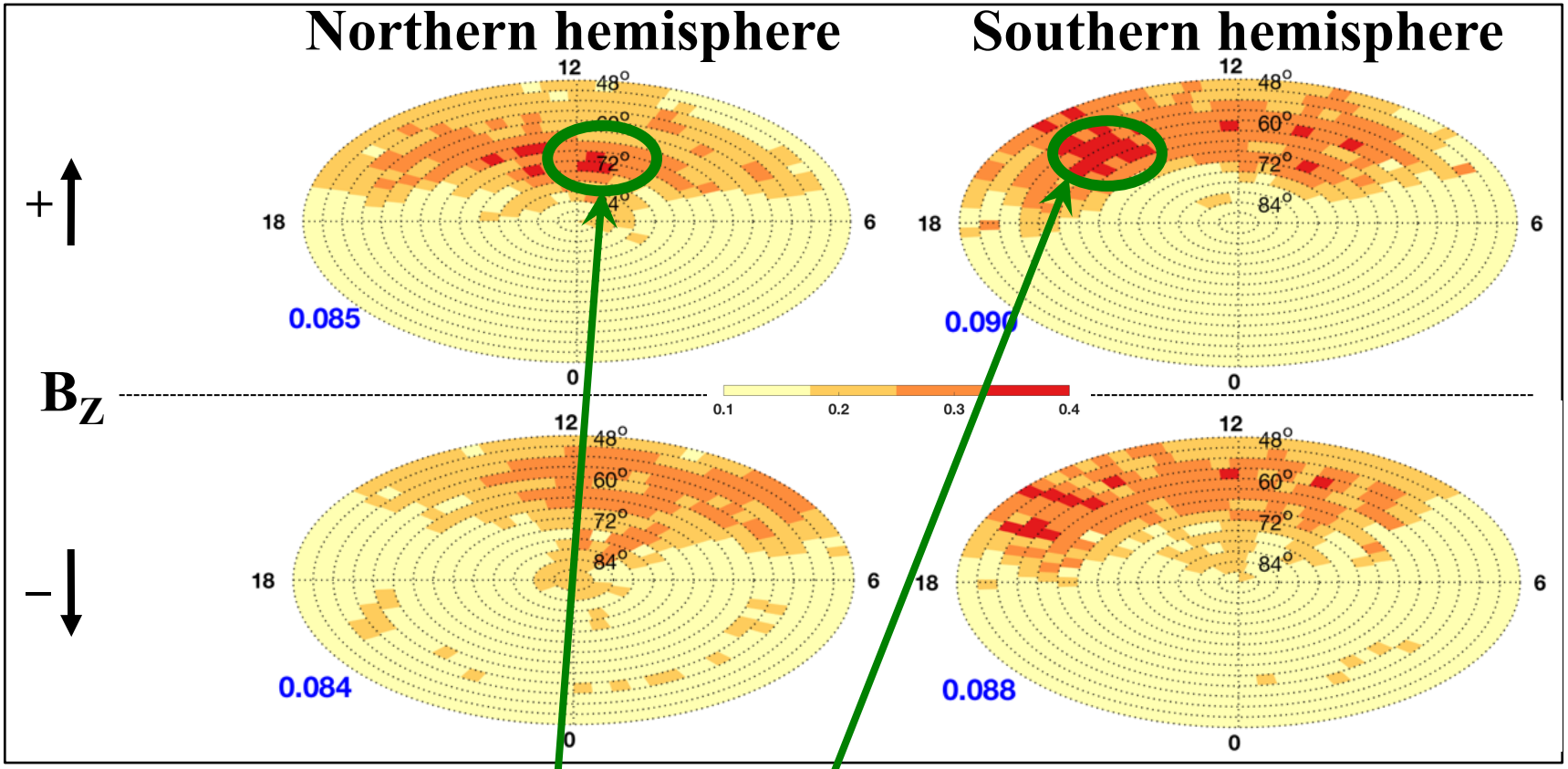
How connected a grid point is to the rest of the network

➔ Larger = greater influence on network function

Network analysis

Degree Centrality

New Frontier: Network analysis - Multi-scale - Exciting future

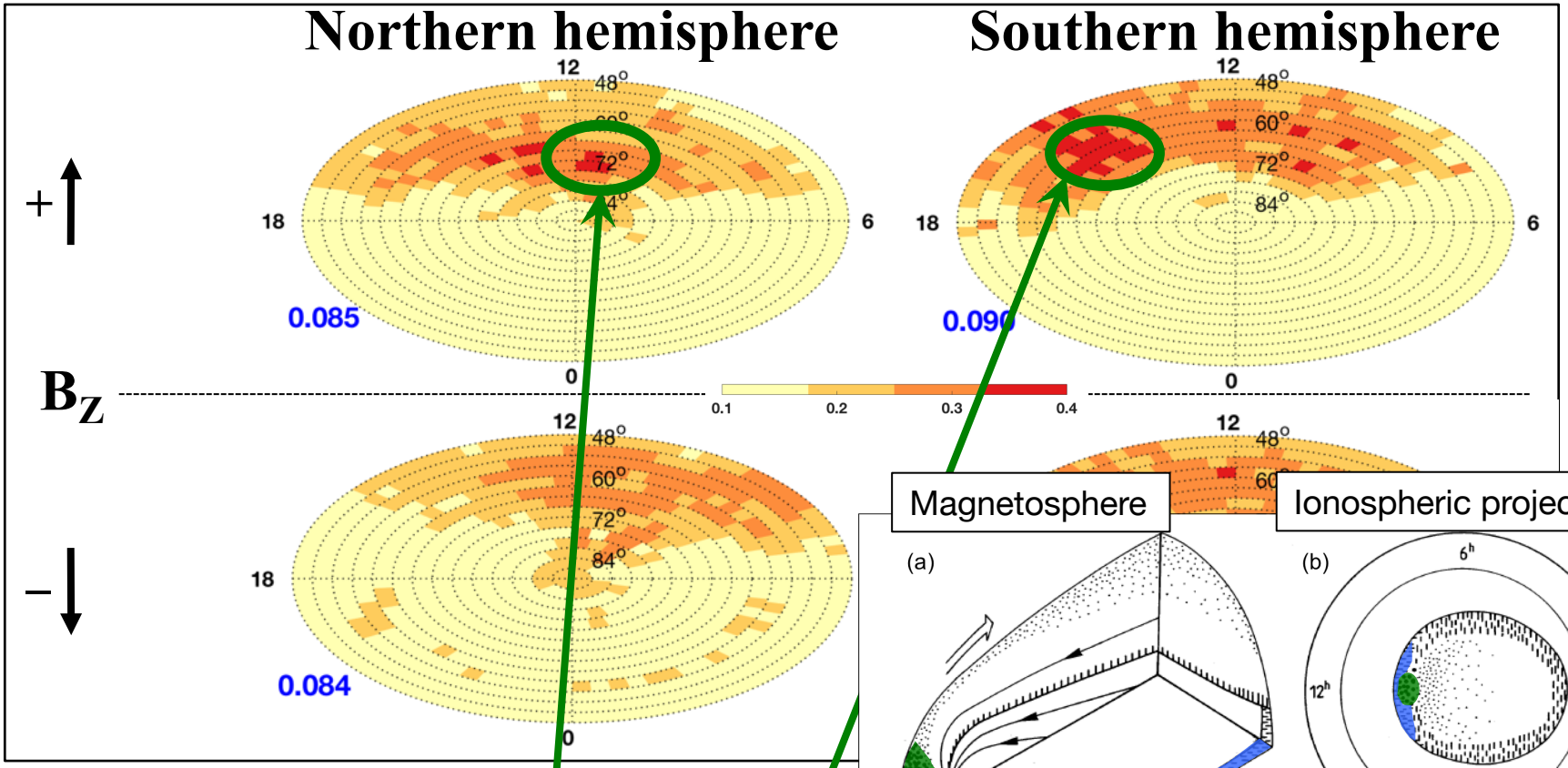


Cusp and ionospheric projection of magnetospheric boundary layers different between hemispheres

Network analysis

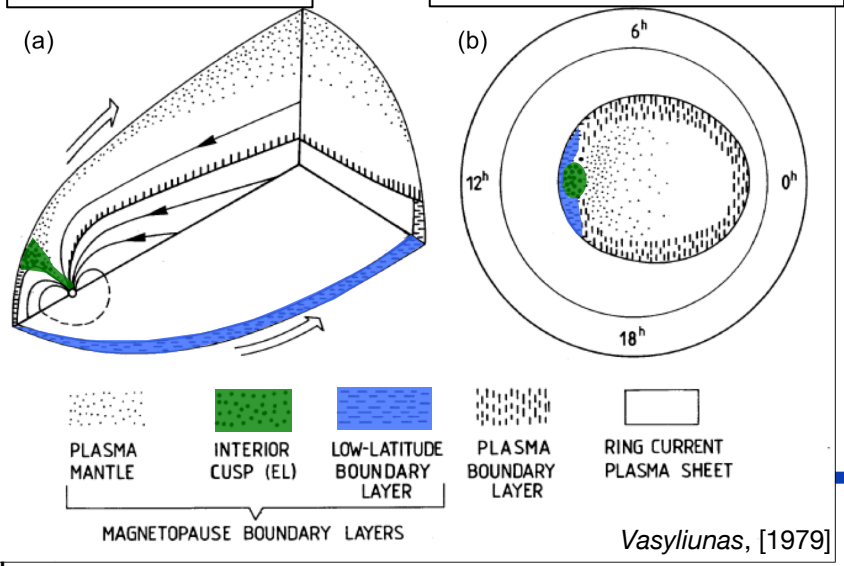
Degree Centrality

New Frontier: Network analysis - Multi-scale - Exciting future



Magnetosphere

Ionospheric projection



Vasyliunas, [1979]

Cusp and ionospheric projection of magnetospher
hemispheres

Network analysis

Degree Centrality

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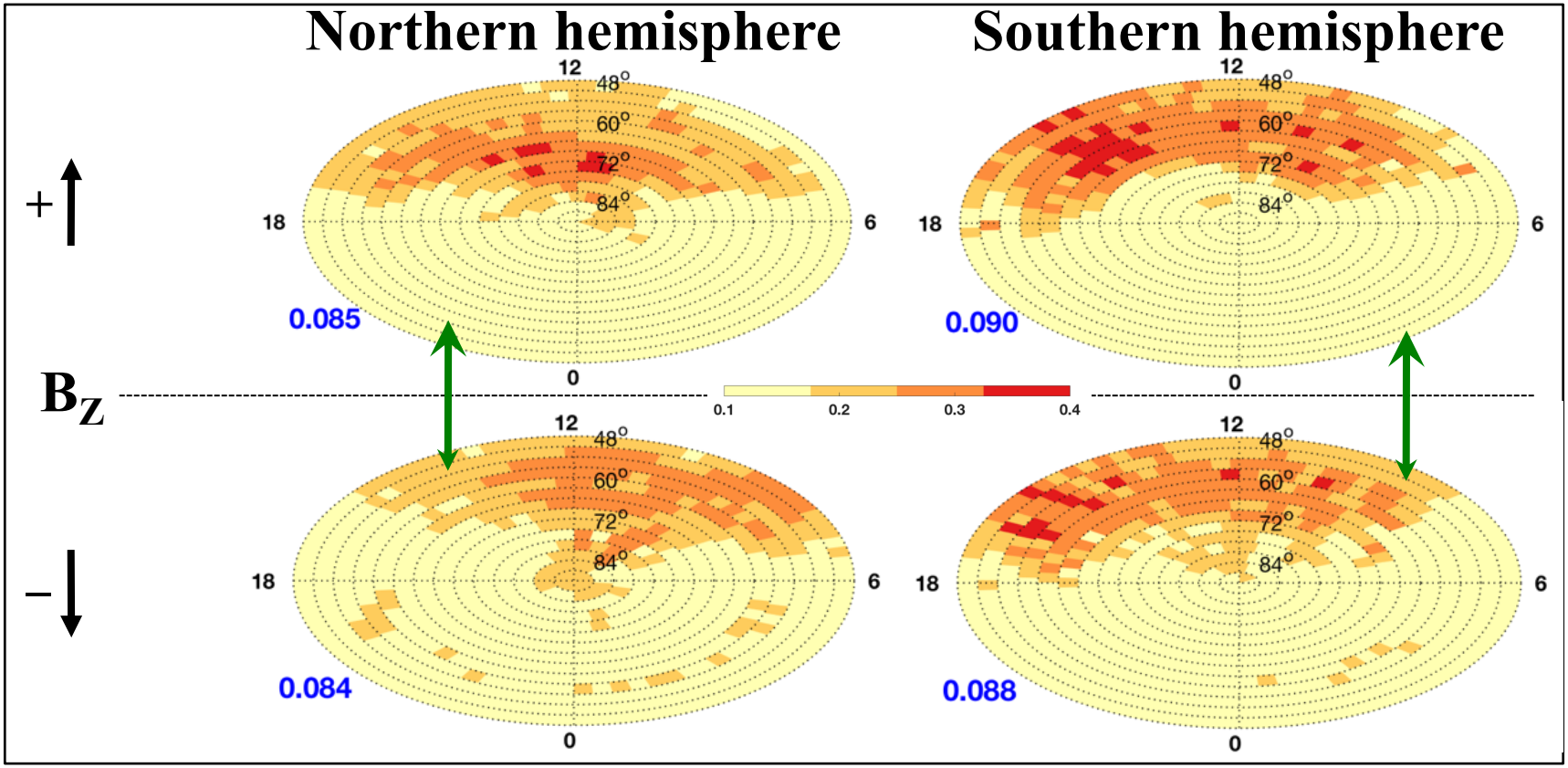


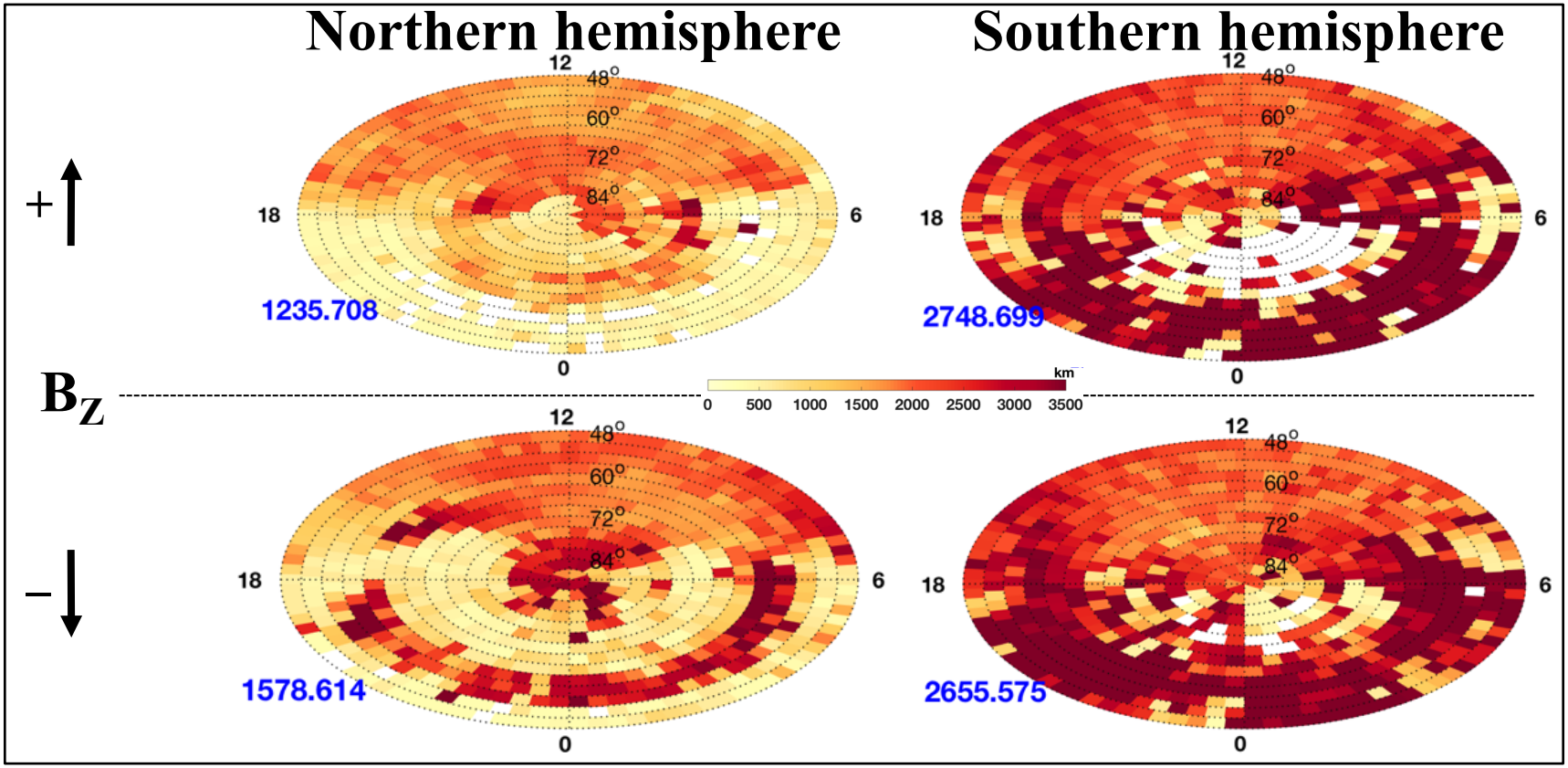
Cusp and ionospheric projection of magnetospheric boundary layers not as influential in summer hemisphere

Dayside is more important to functioning of the network during local winter

Network analysis

Median Connection Distance

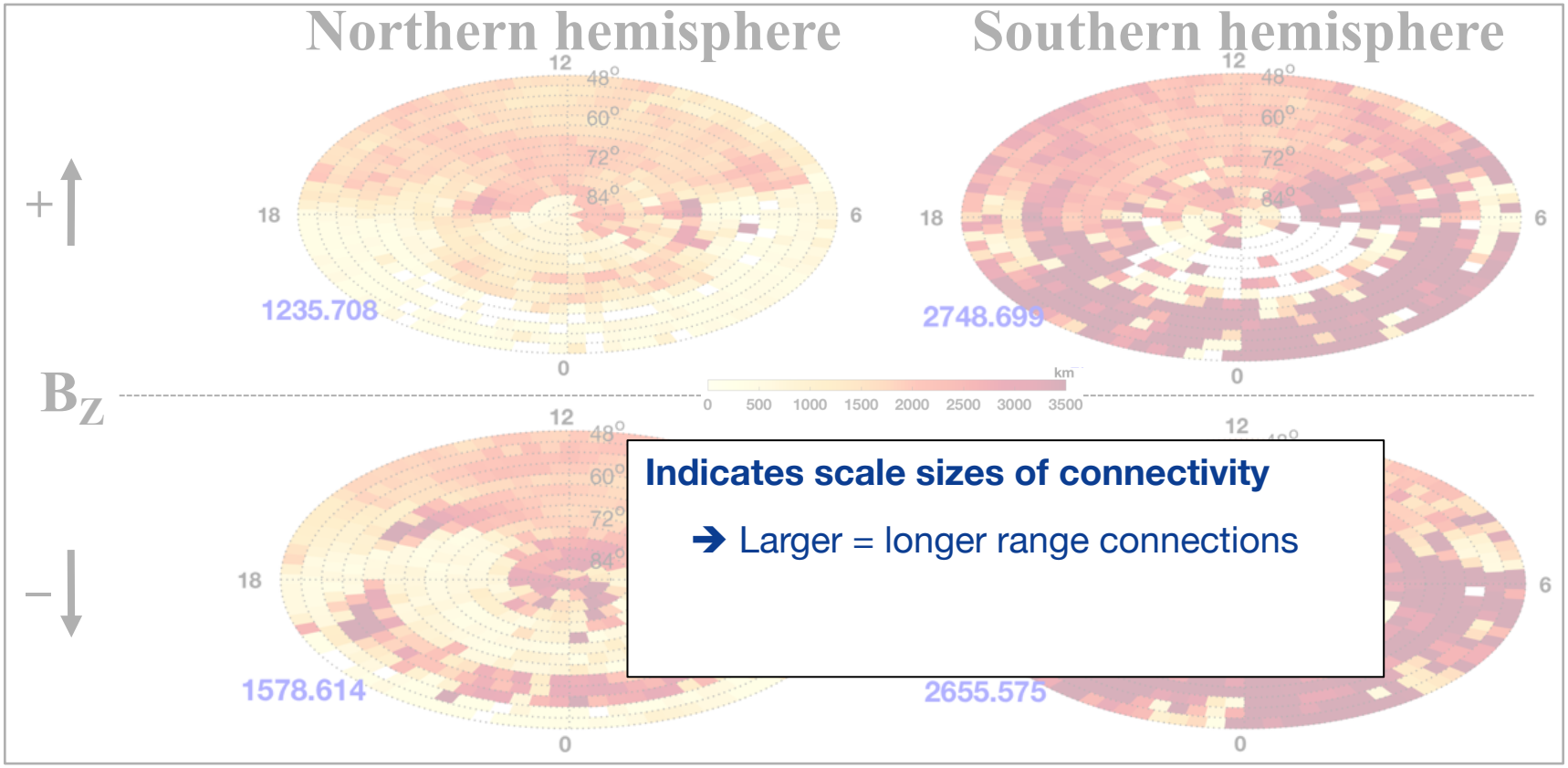
New Frontier: Network analysis - Multi-scale - Exciting future



Network analysis

Median Connection Distance

New Frontier: Network analysis - Multi-scale - Exciting future



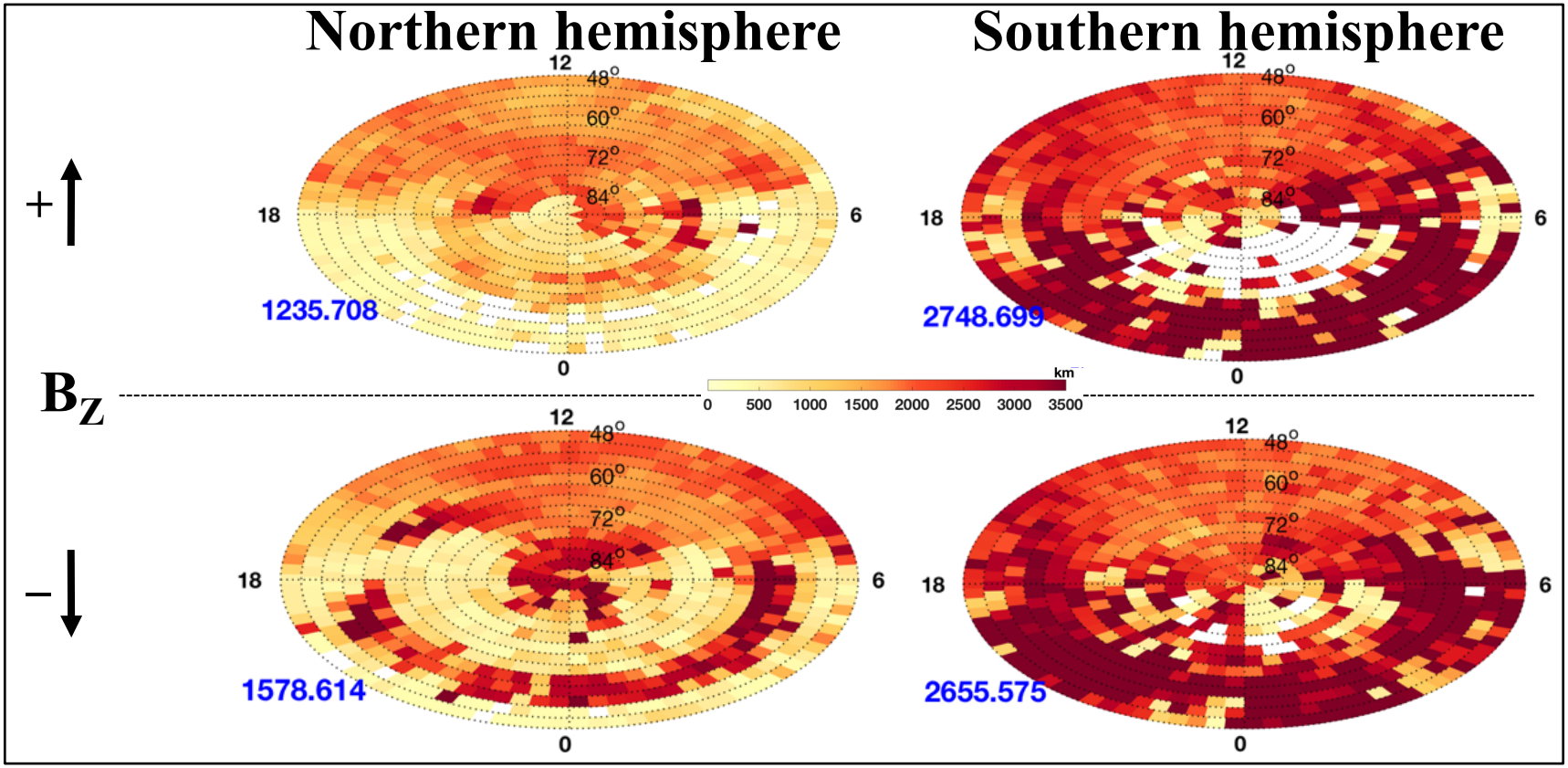
Indicates scale sizes of connectivity

➔ Larger = longer range connections

Network analysis

Median Connection Distance

New Frontier: Network analysis - Multi-scale - Exciting future

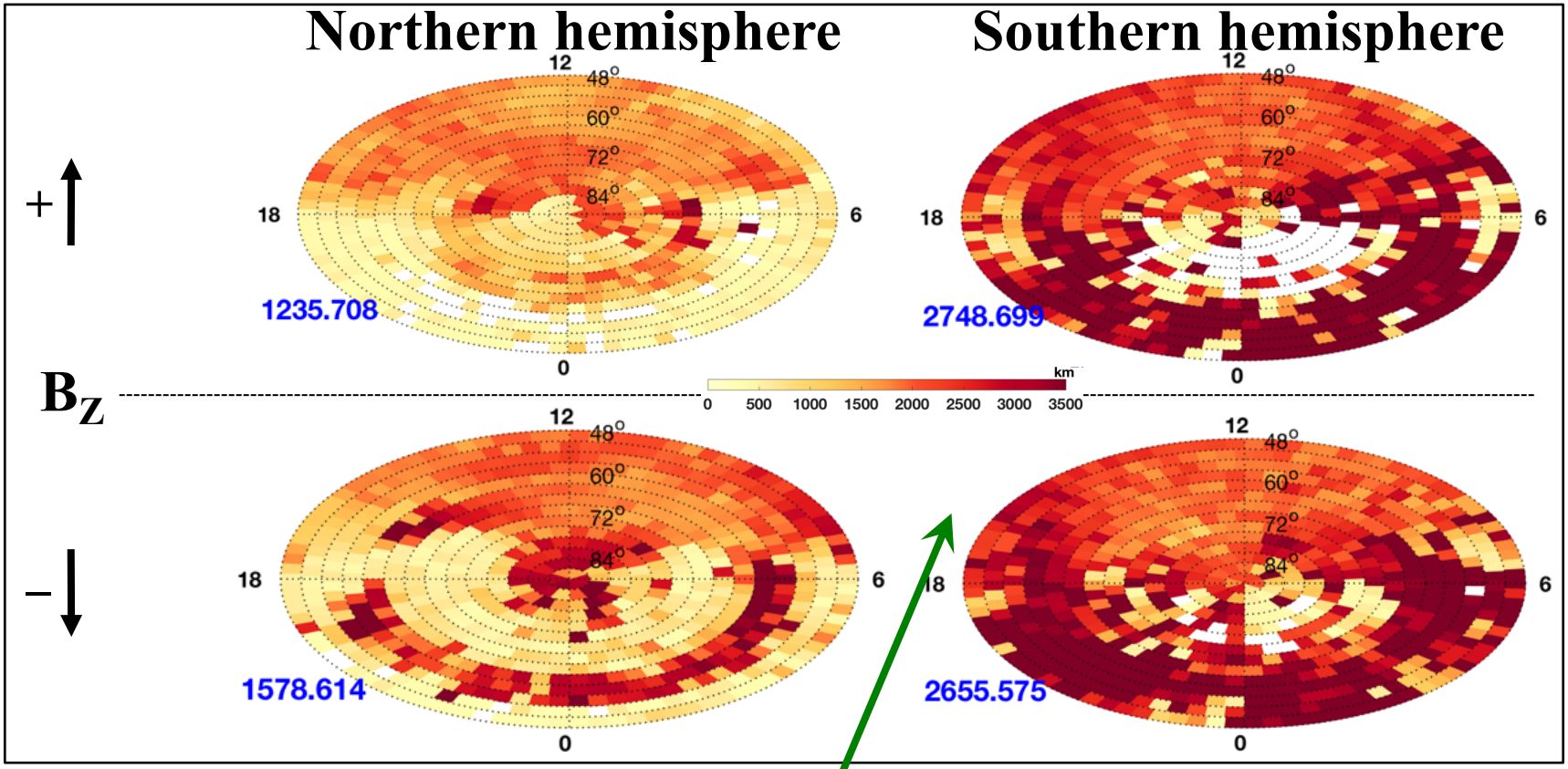


Hemispheric asymmetries clear

Network analysis

Median Connection Distance

New Frontier: Network analysis - Multi-scale - Exciting future



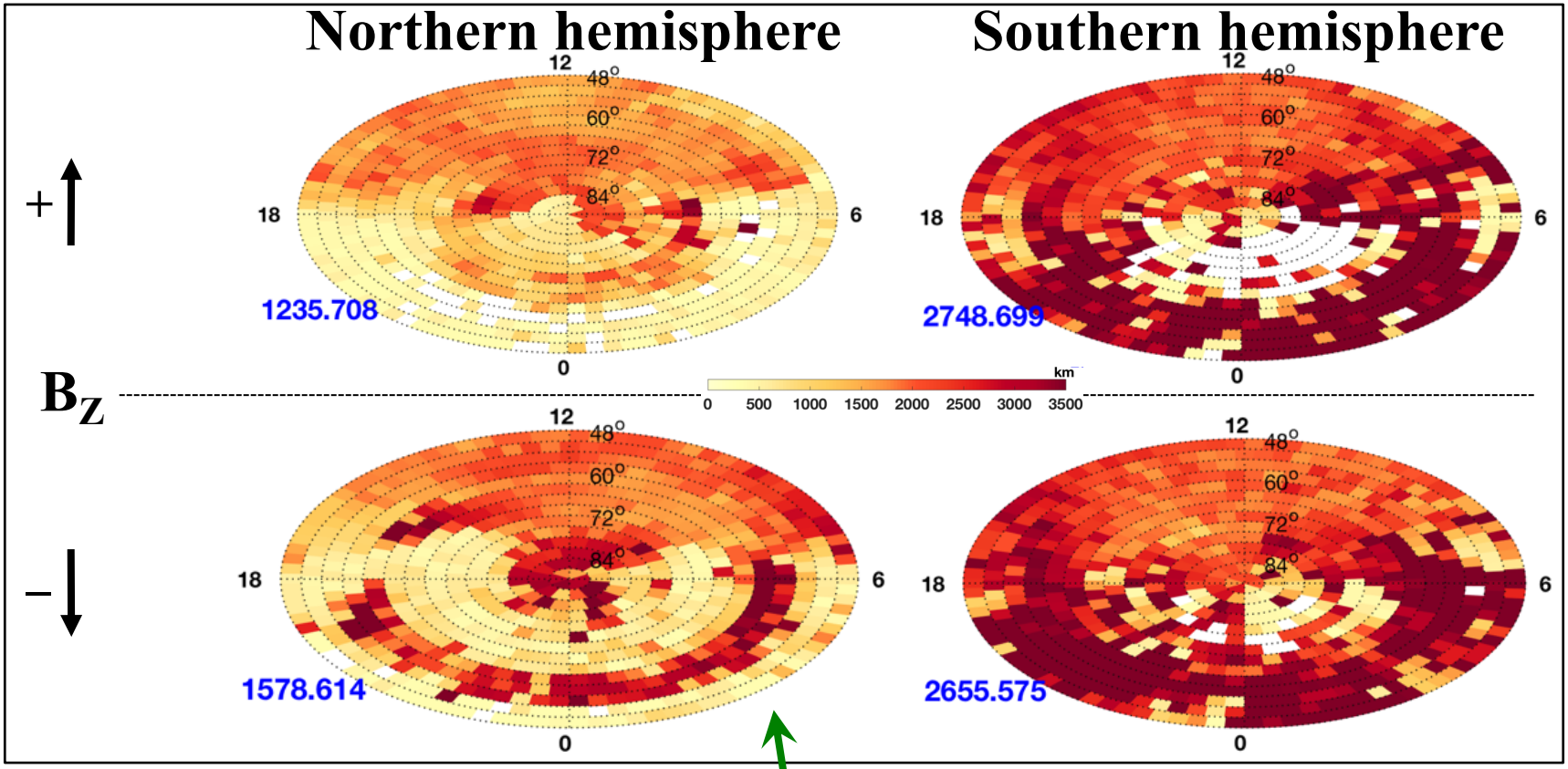
Hemispheric asymmetries clear

Longer range connections in southern hemisphere

Network analysis

Median Connection Distance

New Frontier: Network analysis - Multi-scale - Exciting future



Hemispheric asymmetries clear

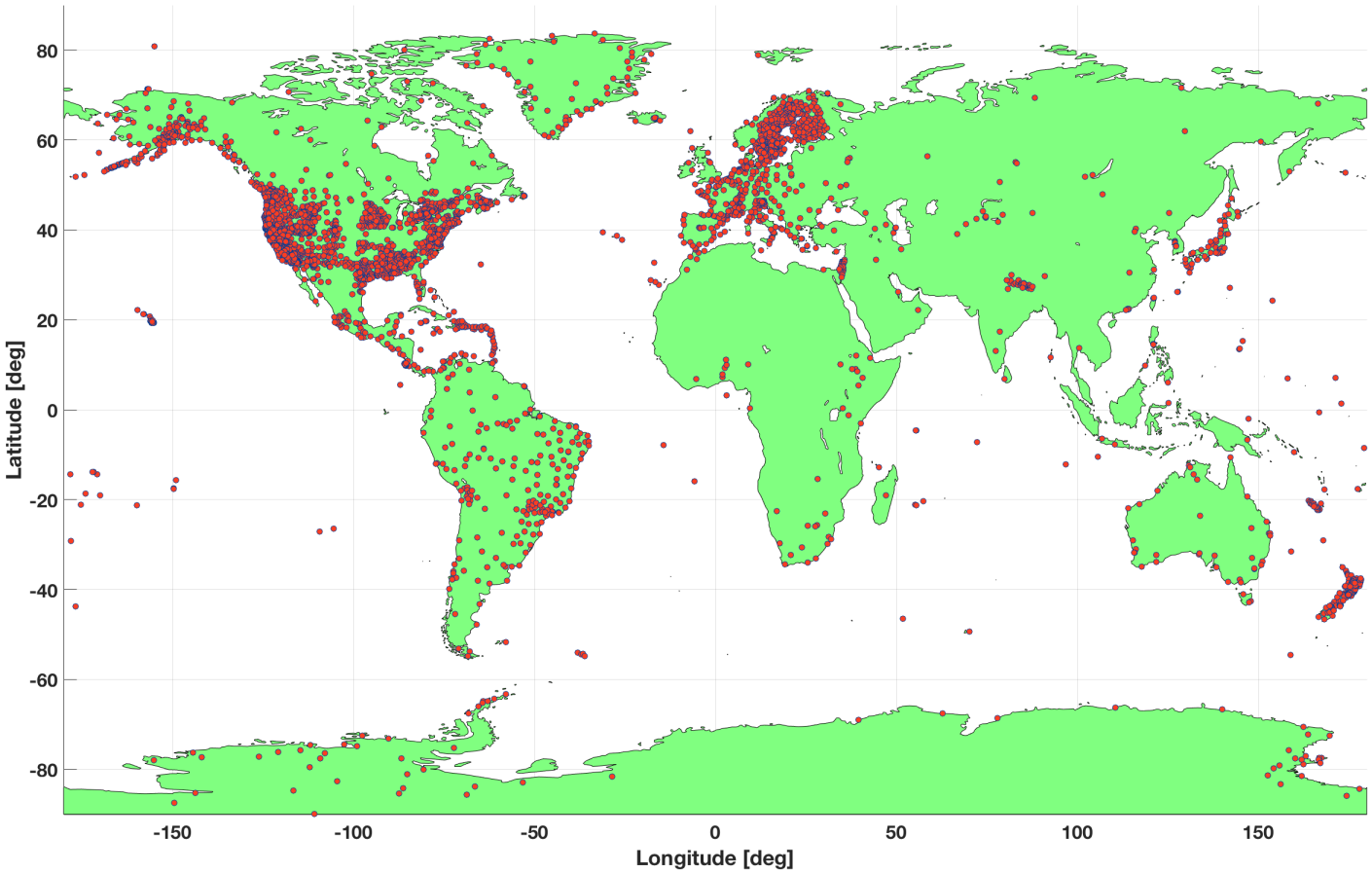
Longer range connections in southern hemisphere

IMF dependency greater in northern hemisphere

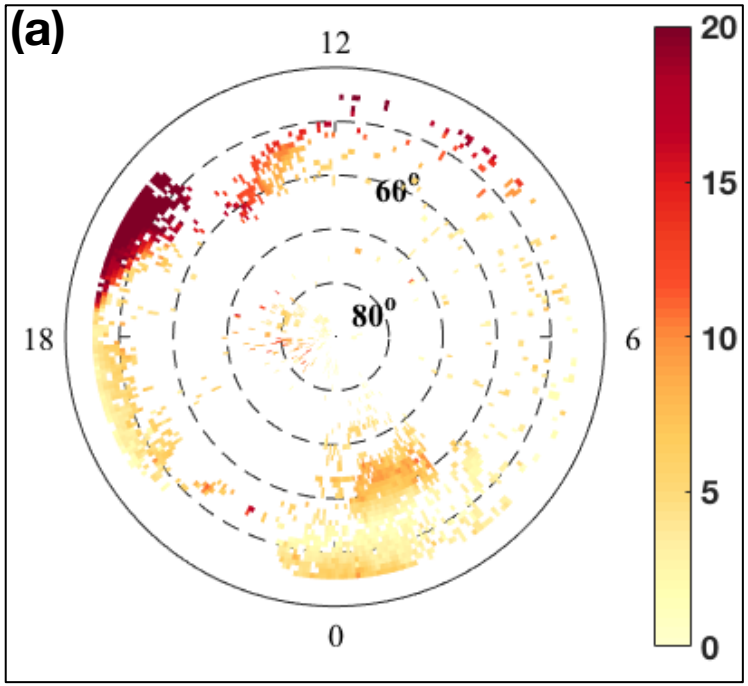
Network analysis

Networks suggest GNSS signals contain information about MI coupling

Characteristic distribution of GPS ground-based receivers

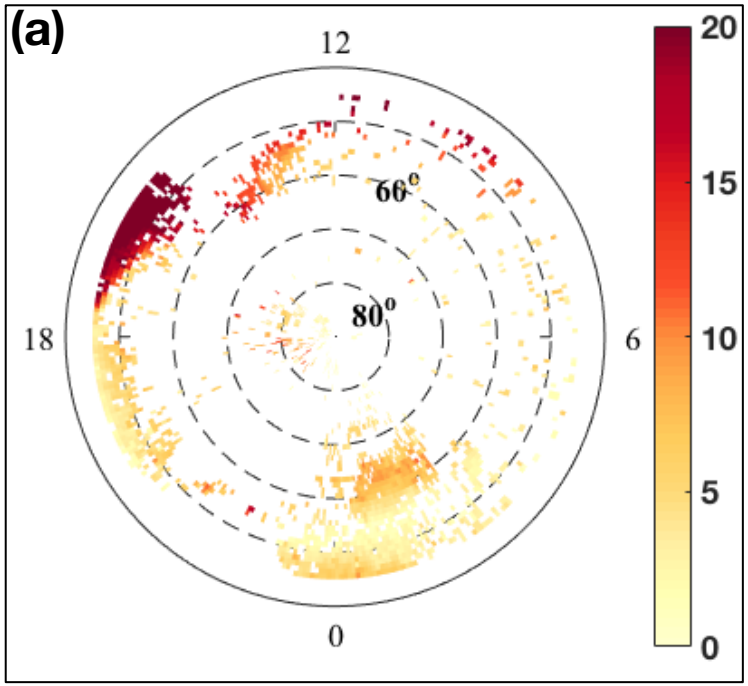


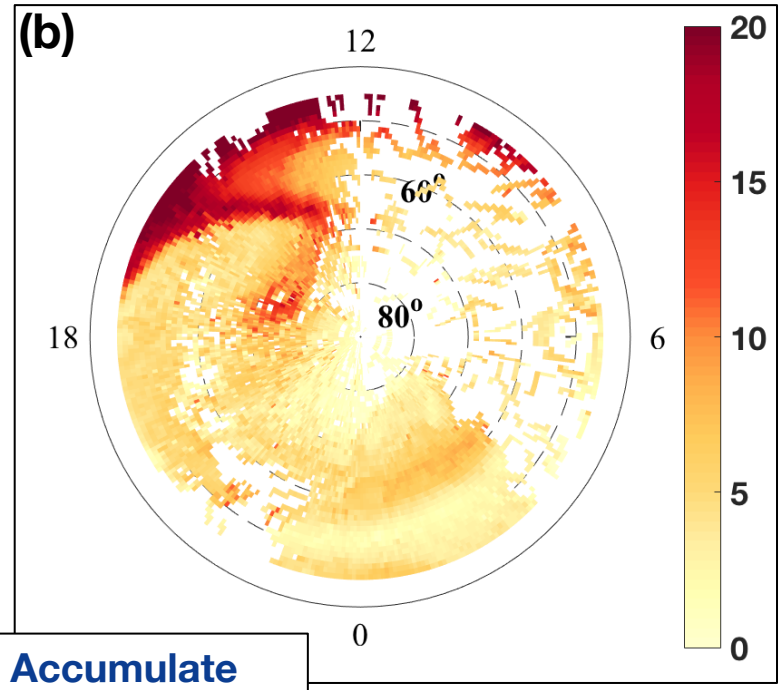
Network analysis: Steps



Start with TEC data (1°x1° geographic coordinates at 5-minute cadence) converted to magnetic coordinates

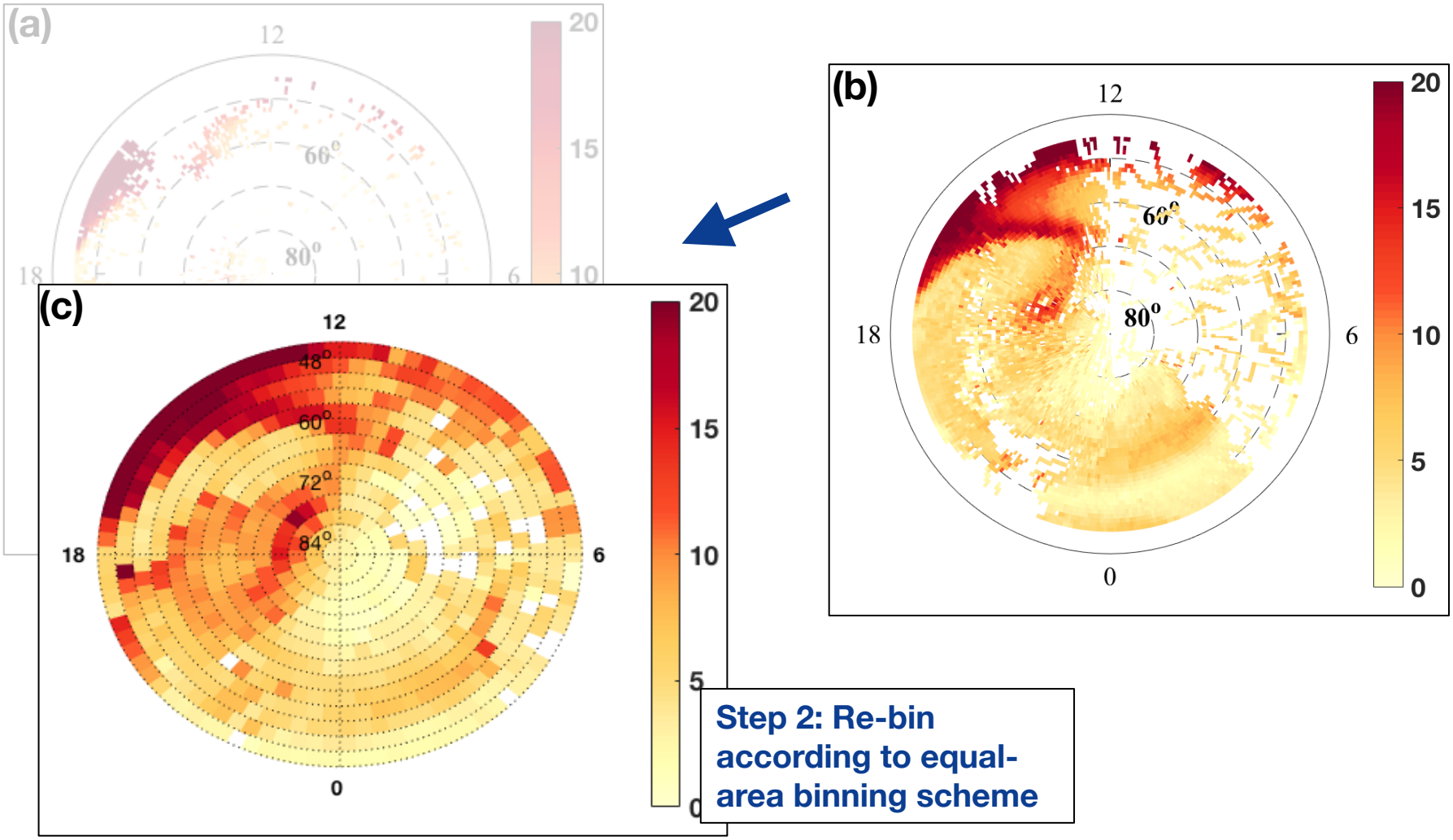
Network analysis: Steps





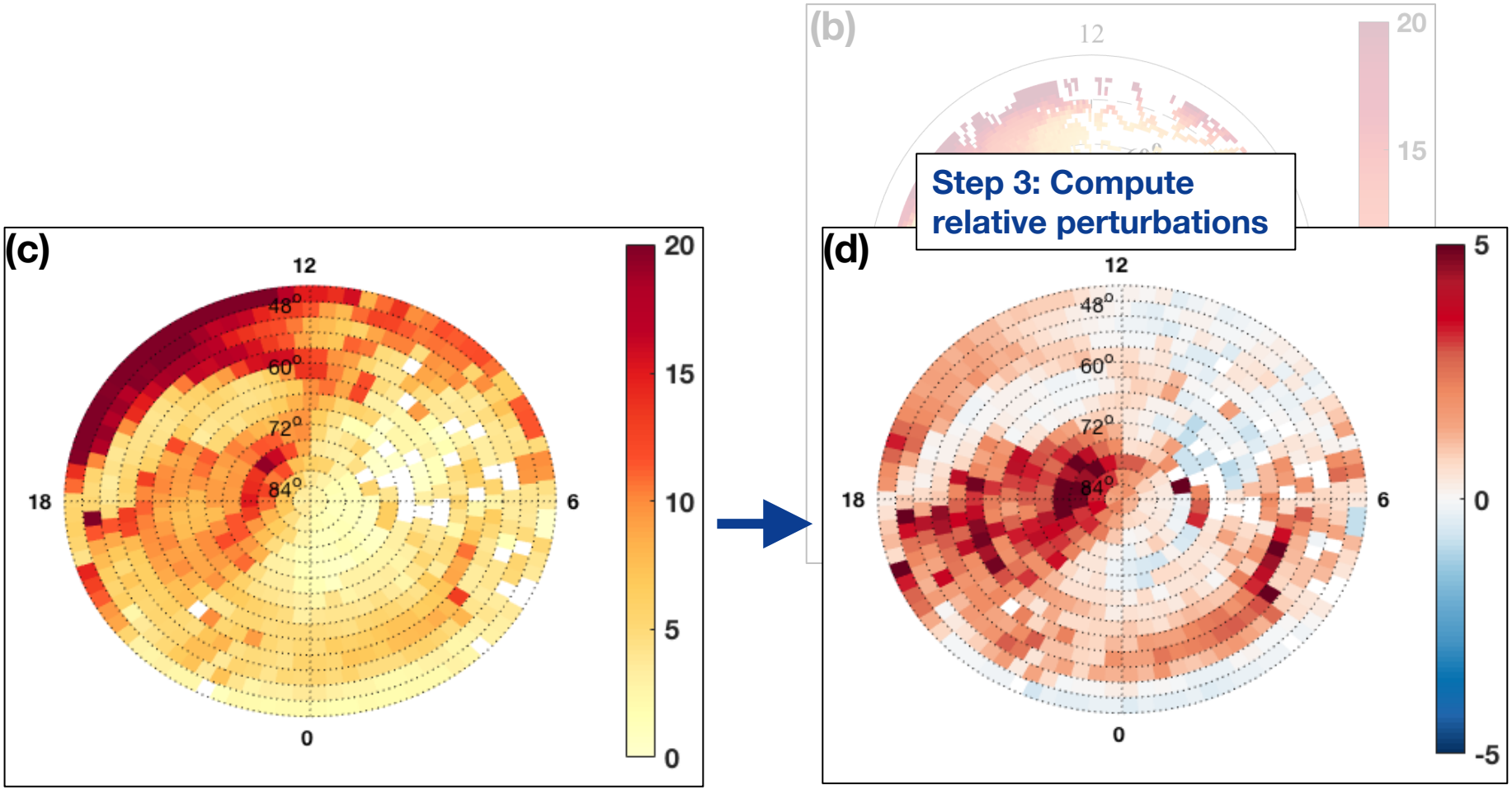
Step 1: Accumulate TEC data over 1-hour time span

Network analysis: Steps



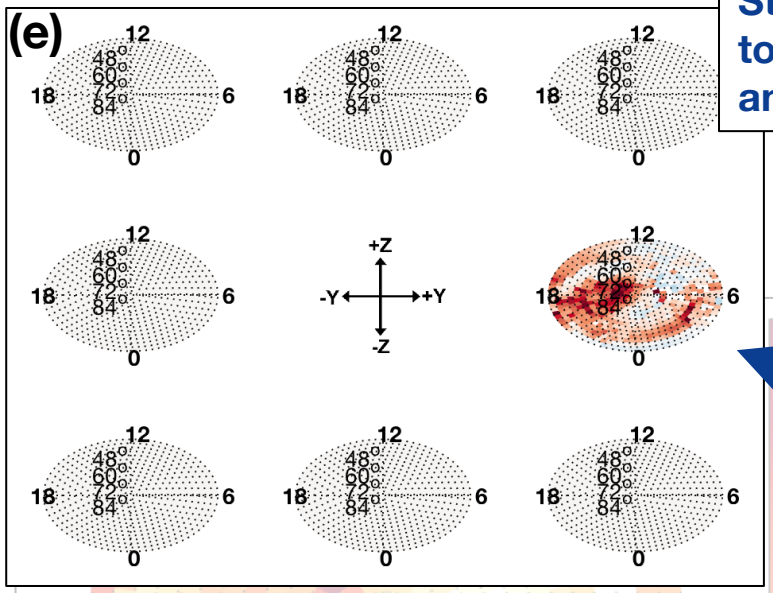
Step 2: Re-bin according to equal-area binning scheme

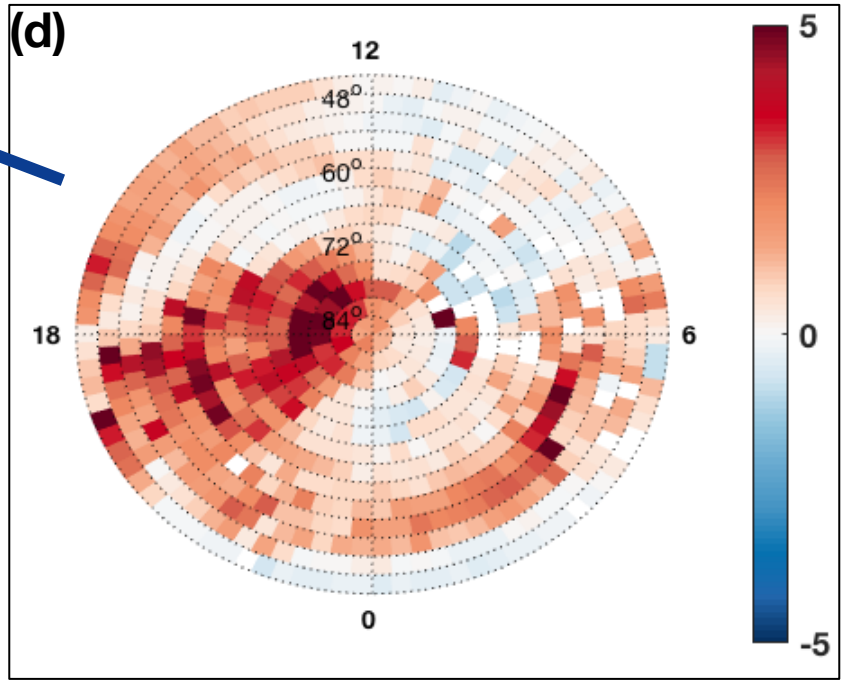
Network analysis: Steps



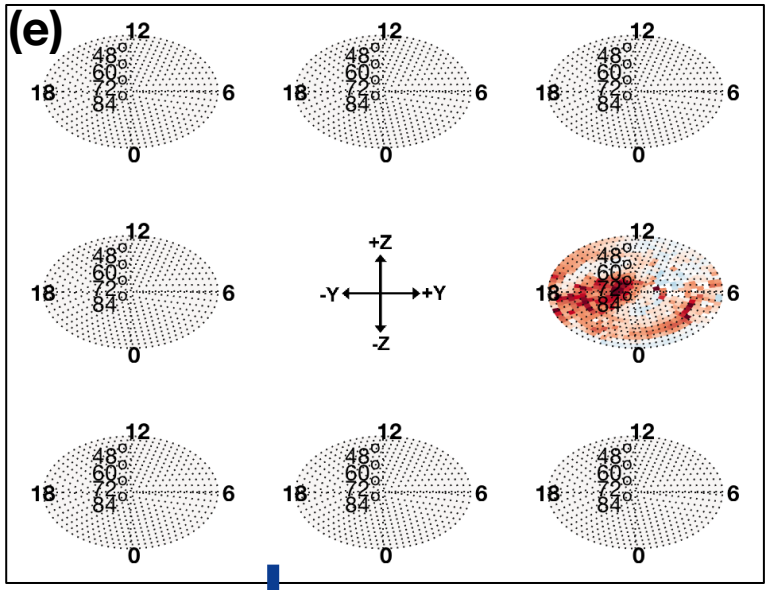
Network analysis: Steps

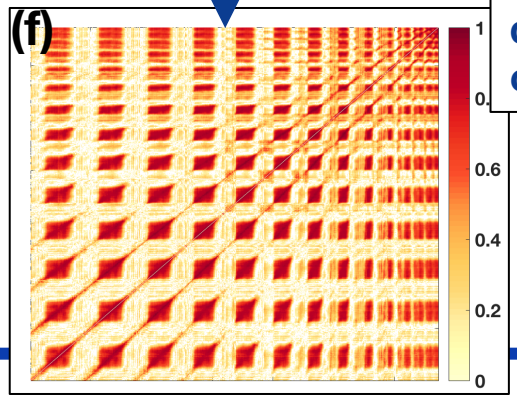
Step 4: Assign distribution to appropriate IMF clock angle bin



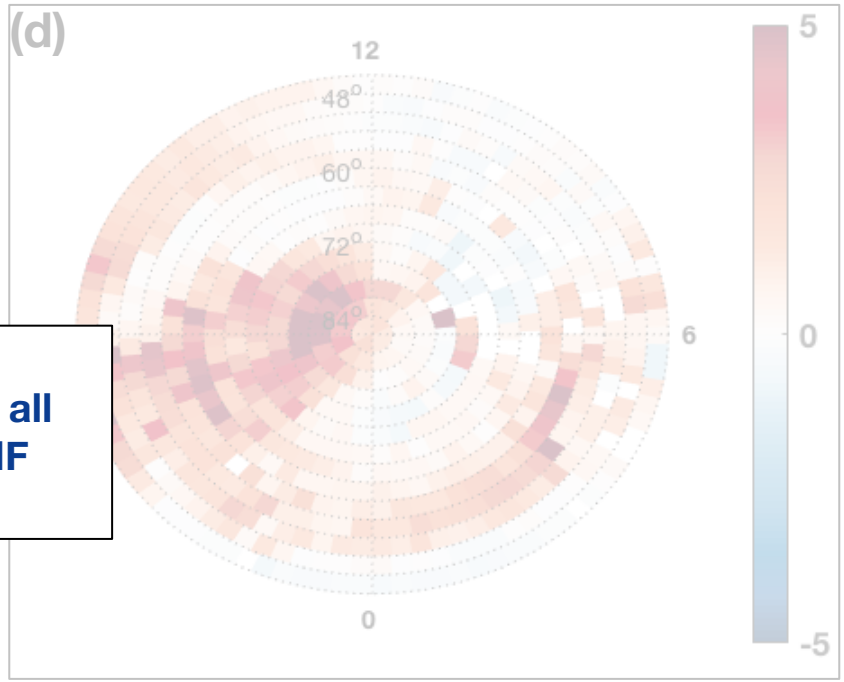


Network analysis: Steps

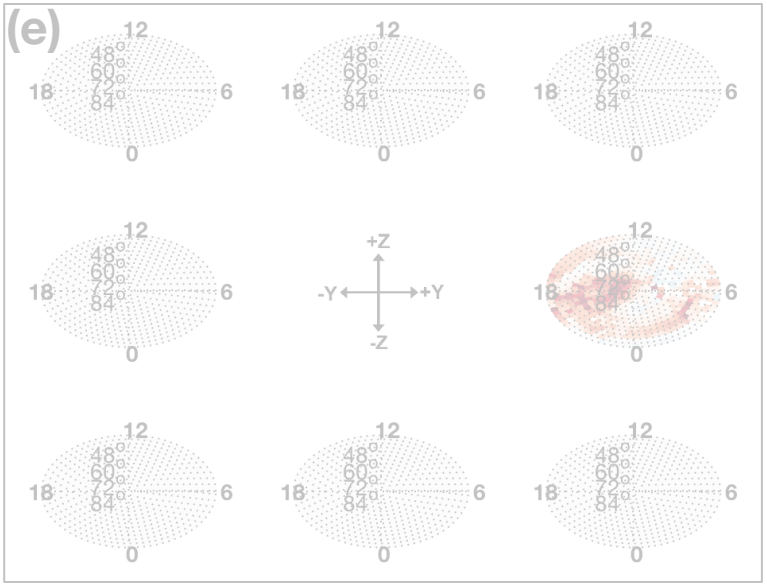




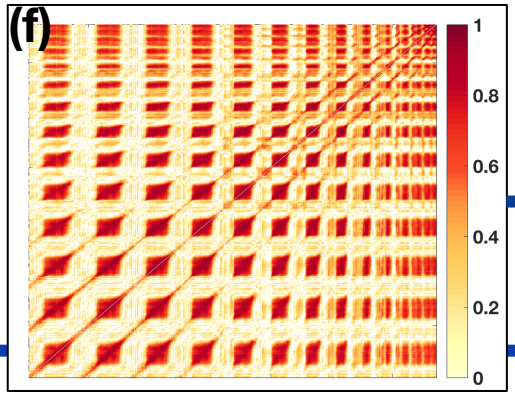
Step 5: Calculate correlation matrix from all distributions in each IMF clock angle bin

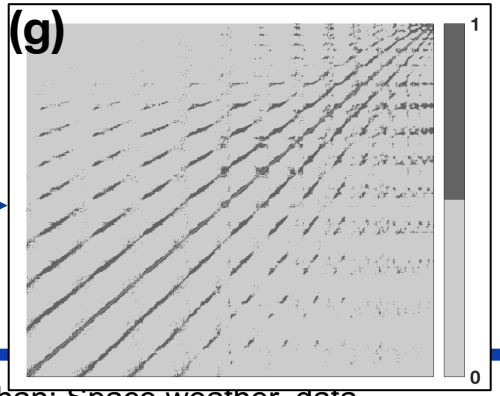


Network analysis: Steps

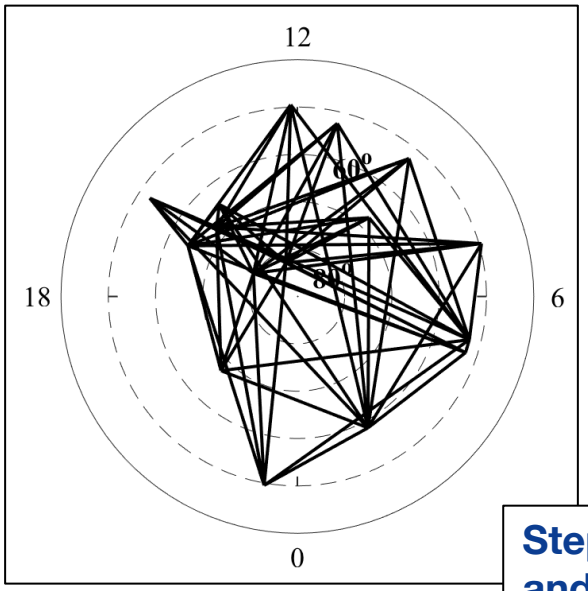


Step 6: Calculate adjacency matrix

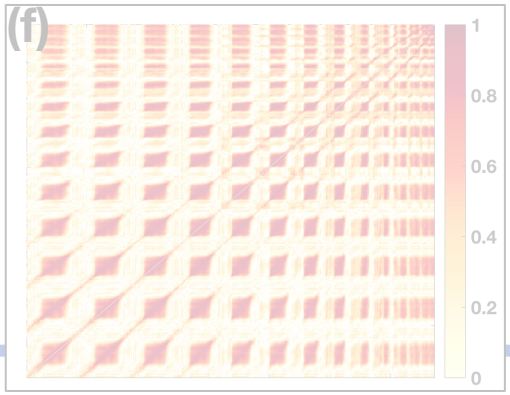


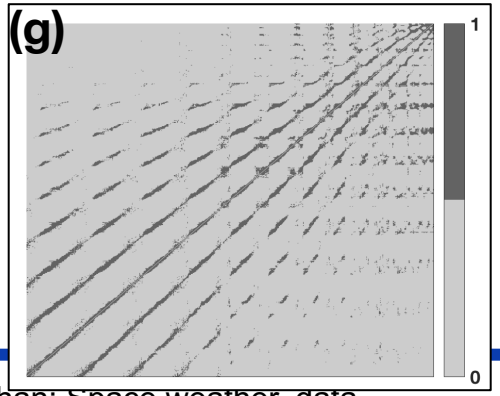


Network analysis: Steps



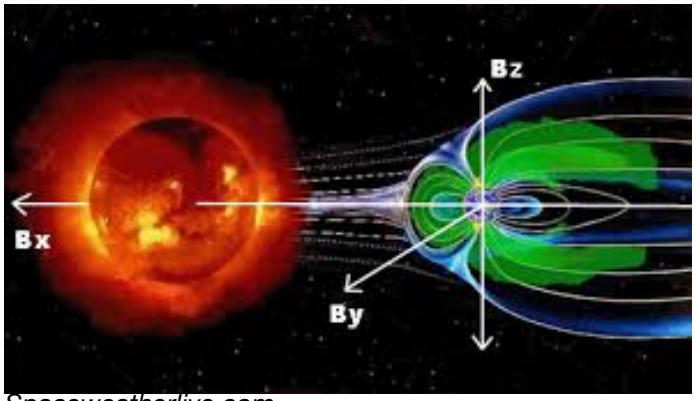
Step 7: Construct and visualize the network



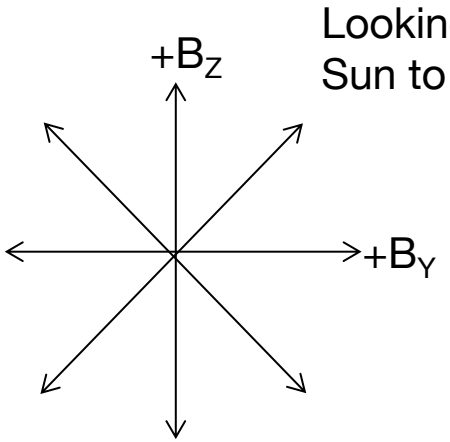


How are we carrying out this analysis?

Hemispheric specific, IMF-dependent TEC (Jan. 2016)

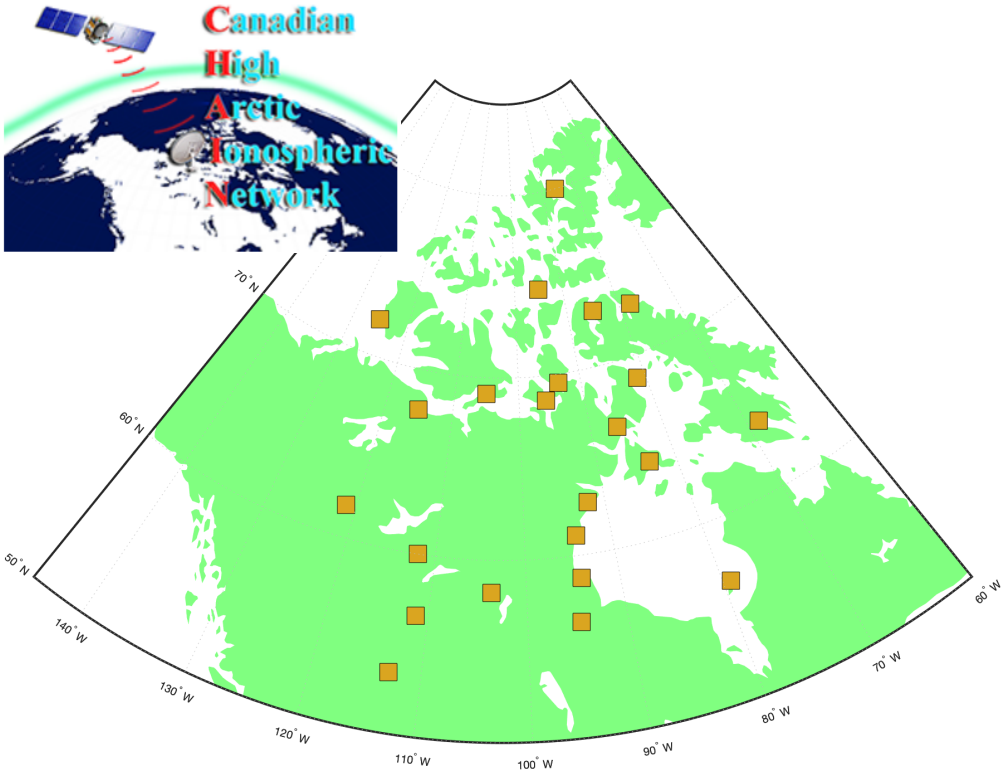


Spaceweatherlive.com



Looking from Sun to Earth

Exciting possibilities:
Machine Learning



Given ionospheric, geomagnetic, and solar information *now…*

Can we predict ionospheric scintillation in *one hour*?

t → ***t+1 hour***

45

Number of features in each data sample at *t*

Canadian High Arctic Ionospheric Network (CHAIN) GNSS data

Solar wind data and solar indices

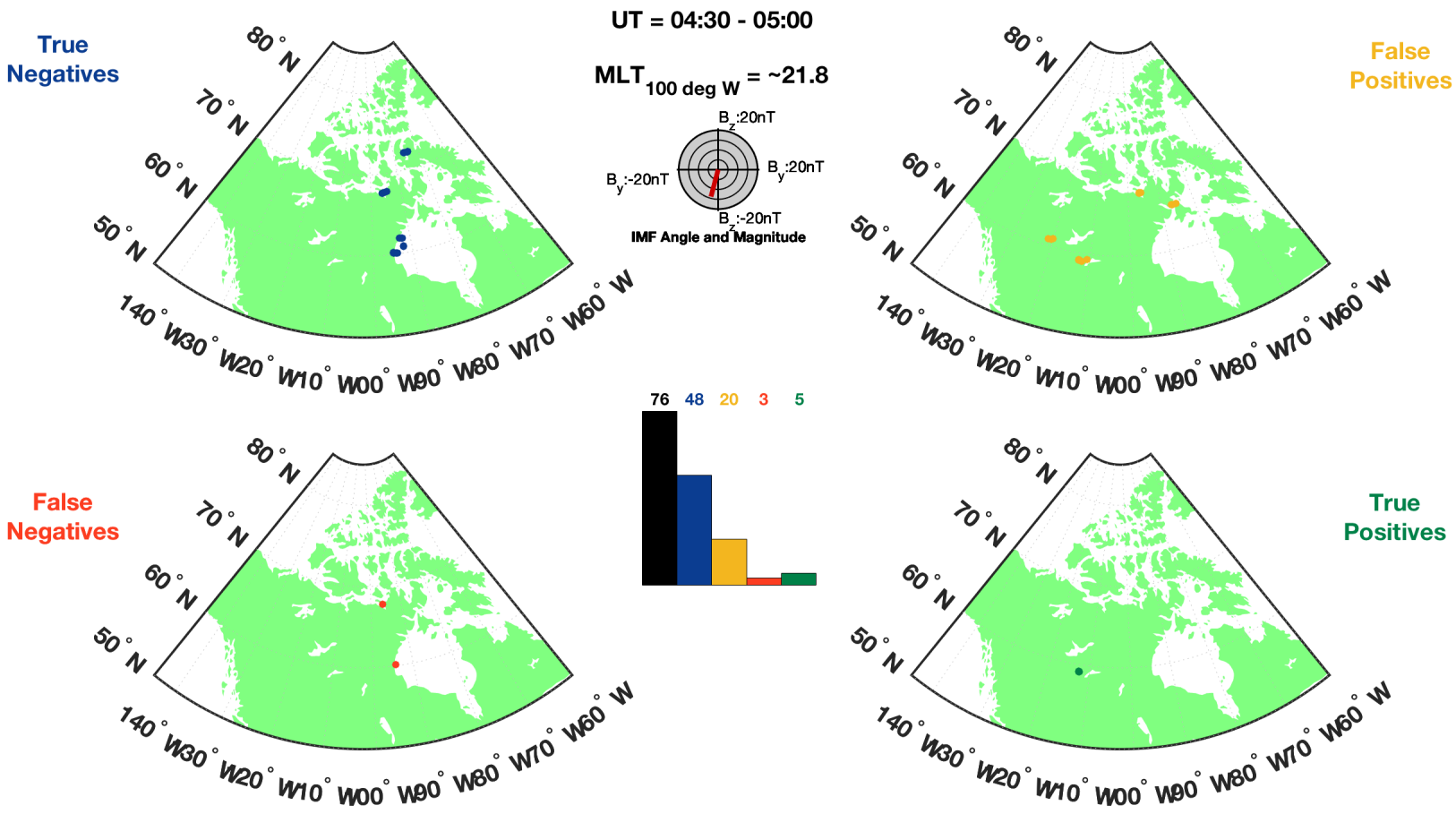
Geomagnetic activity data

Classify

+/- **Scintillation or not at *t+1***

(+) Scintillation > 0.1

(–) No Scintillation < 0.1


True Negatives
False Positives
False Negatives
True Positives
UT = 04:30 - 05:00
MLT100 deg W = ~21.8
Bz:20nT
By:-20nT
By:20nT
Bz:-20nT
IMF Angle and Magnitude
76 48 20 3 5
80 ° N
70 ° N
60 ° N
50 ° N
140 ° W30 ° W20 ° W10 ° W00 ° W90 ° W80 ° W70 ° W60 ° W

STRETCHING GNSS SIGNALS FOR SPACE WEATHER DISCOVERY

JPL

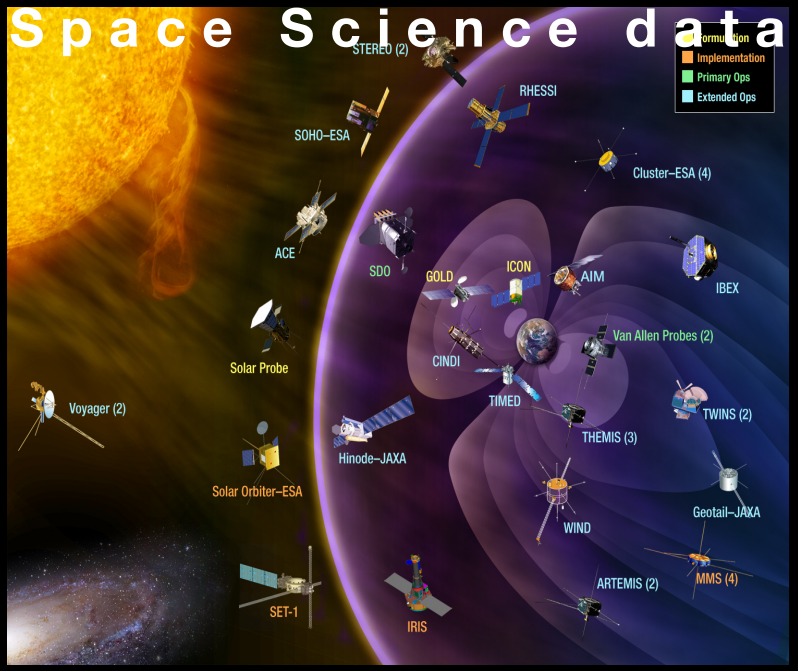
Ryan McGranaghan, Anthony Mannucci
University Corporation for Atmospheric Research (UCAR)
NASA Jet Propulsion Laboratory, California Institute of Technology

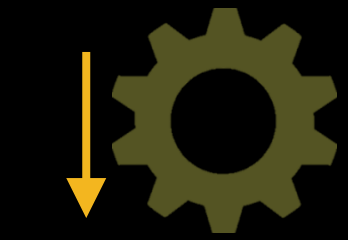
Brian Wilson, Chris Mattmann, Sujen Shah, Huikyo Lee
NASA Jet Propulsion Laboratory, California Institute of Technology

Interagency, Intra-agency and International efforts

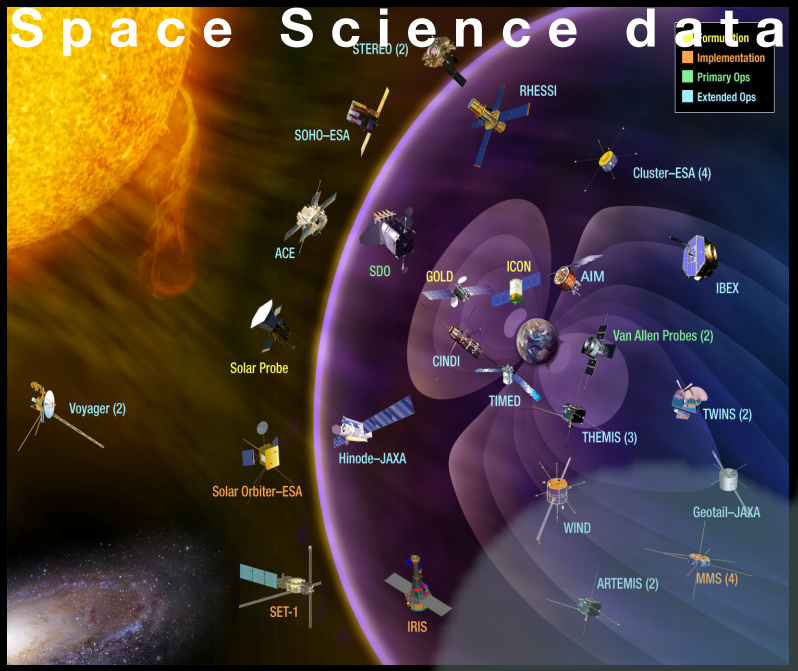
- NASA–NSF (NASA-NSF MOU)
  - Co-funding CCMC facility
  - Co-funding Living With a Star Strategic Capabilities
  - New opportunity focused on "Computational Aspects of Space Weather"
  - Coordinating ICON & GOLD opportunities (NASA mission GI, NSF CEDAR, joint opp.)
- NASA-NOAA (NASA-NOAA MOU)
  - Collaboration between CCMC and NOAA/SWPC on space weather modeling capability
- NASA-NSF-NOAA
  - Pilot O2R research activity
- Heliophysics-Planetary
  - Co-funding selected Living With a Star grants
  - Joint Juno Participating Scientist Program
- Heliophysics-Astrophysics
  - Joint "Impact of Stellar Properties on the Habitability of Exoplanets" research opportunity
- NASA-ESA
  - Solar Orbiter
  - THOR-US contingent on selection of ESA M5 mission
- NASA-KASI
  - Development towards prototype coronagraph for balloon flight in 2019; agreement signed October 2017

Slide Credit: Peg Luce 2017


Space Science data
Formulation
Implementation
Primary Ops
Extended Ops
STEREO (2)
RHESSI
SOHO–ESA
Cluster–ESA (4)
ACE
SDO
GOLD
ICON
AIM
IBEX
Solar Probe
Van Allen Probes (2)
CINDI
Voyager (2)
TIMED
TWINS (2)
THEMIS (3)
Hinode–JAXA
Solar Orbiter–ESA
Geotail–JAXA
WIND
MMS (4)
ARTEMIS (2)
SET-1
IRIS




Data-Driven Documents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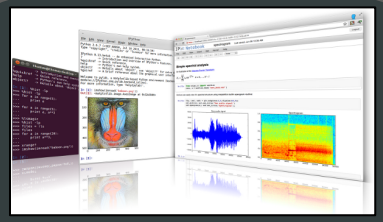
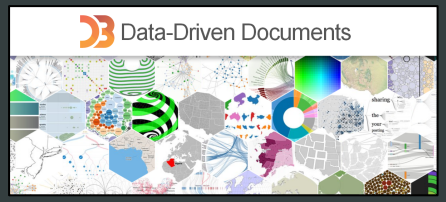
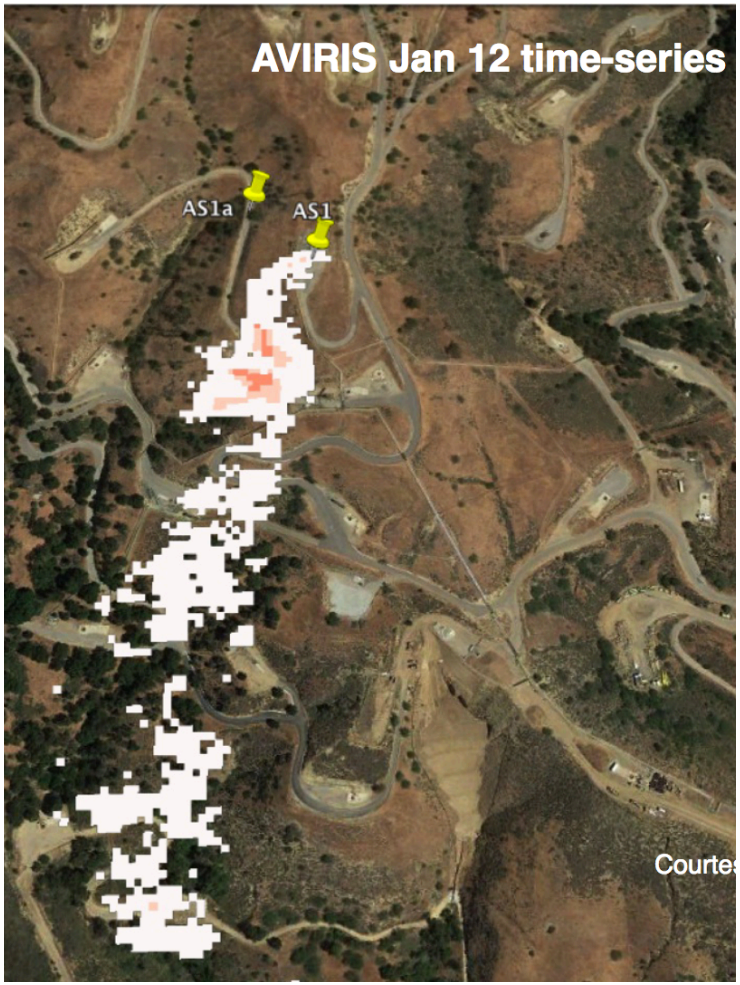



Data-Driven Documents

Methane SourceFinder → Machine learning for geospace imagery data



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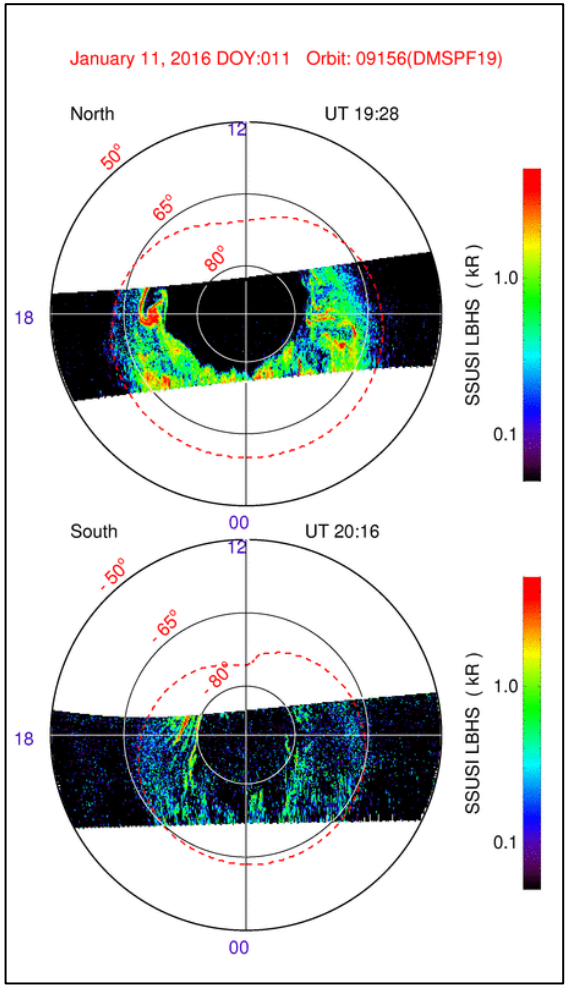
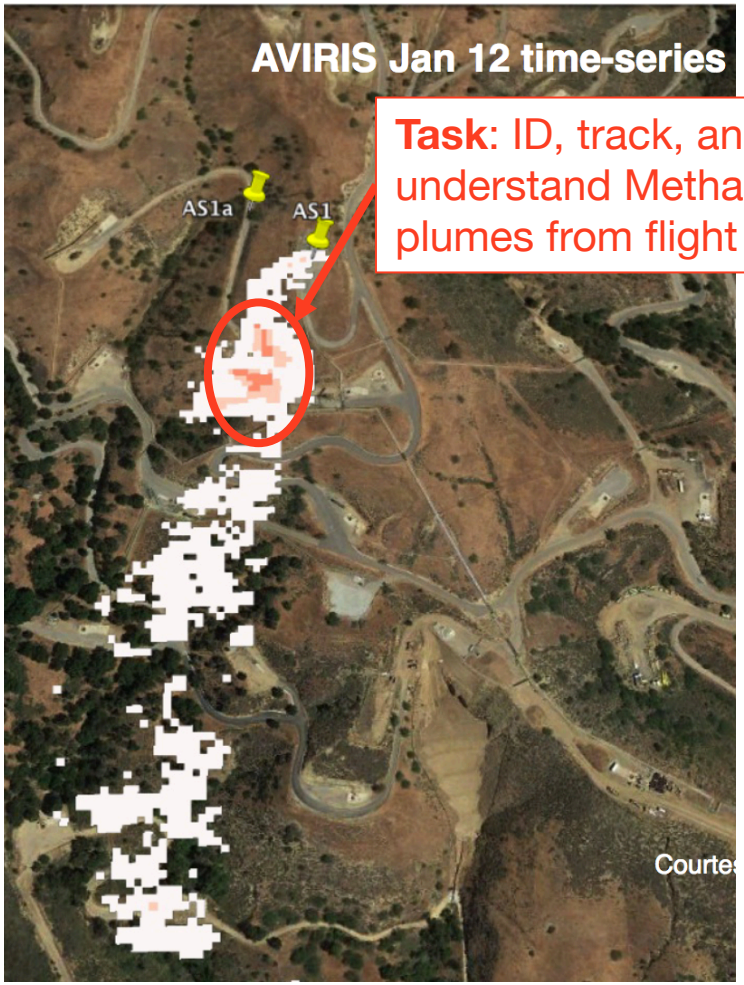


Methane SourceFinder → Machine learning for geospace imagery data



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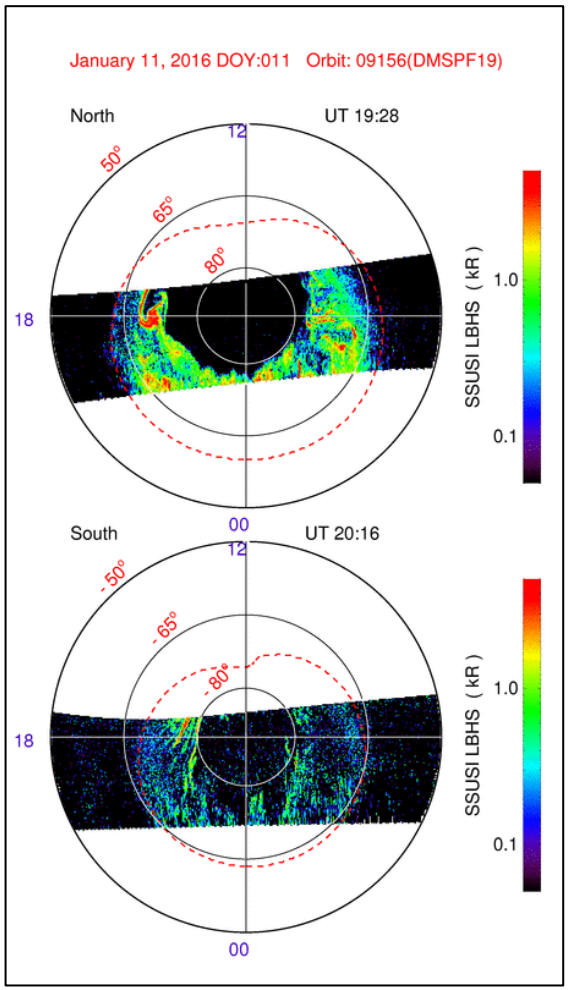

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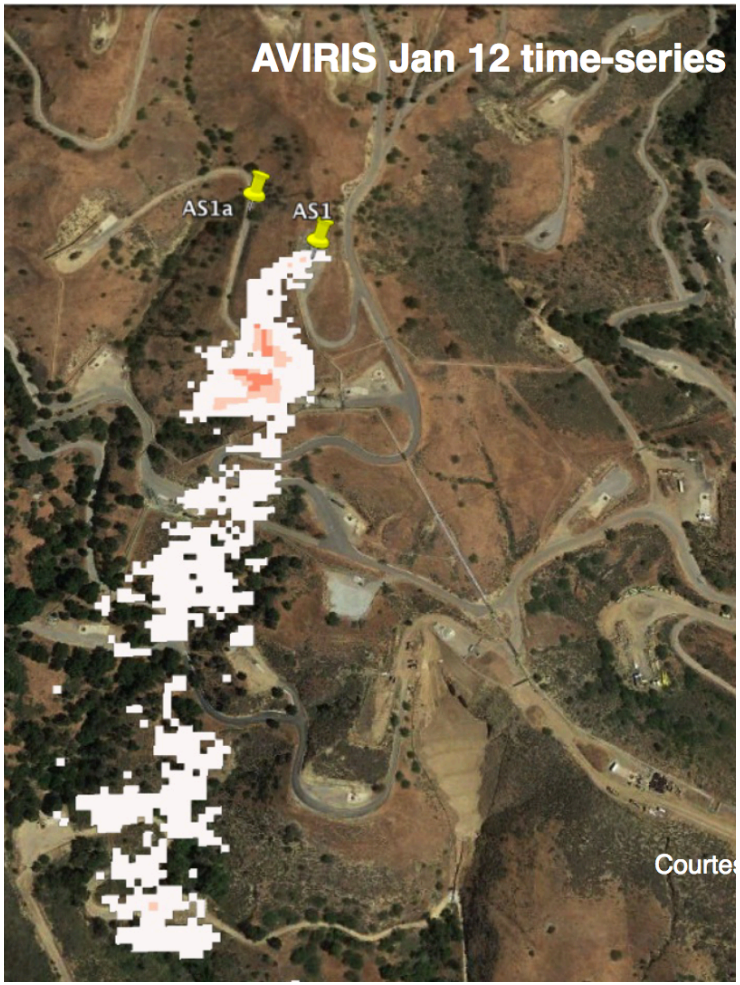

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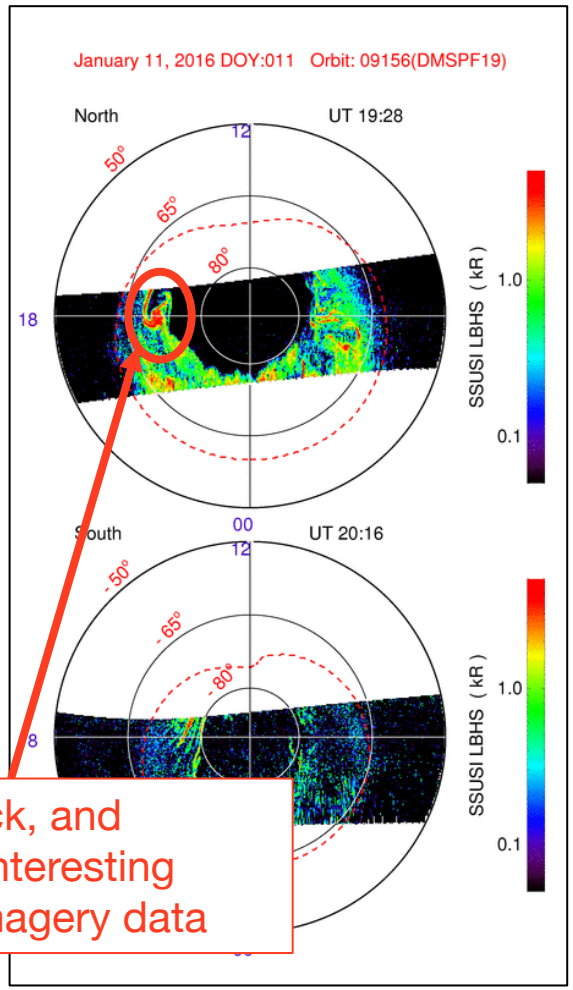
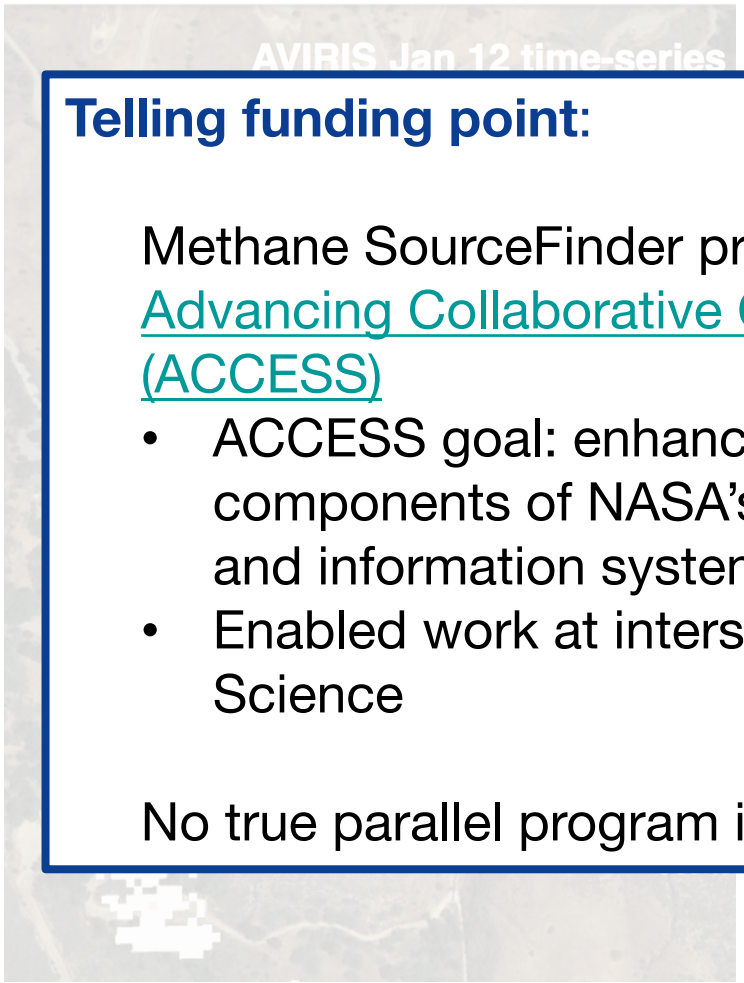
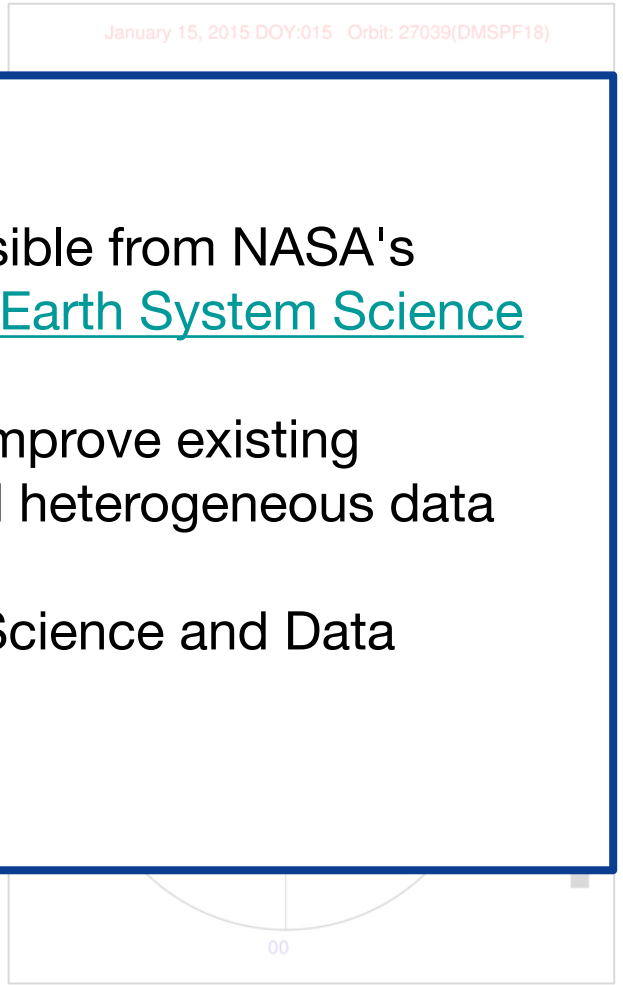


Task: ID, track, and understand interesting features in imagery data

Methane SourceFinder → SSUSI machine learning for ionosphere





Telling funding point:

Methane SourceFinder project made possible from NASA's Advancing Collaborative Connections for Earth System Science (ACCESS)

- ACCESS goal: enhance, extend, and improve existing components of NASA's distributed and heterogeneous data and information systems infrastructure
- Enabled work at intersection of Earth Science and Data Science

No true parallel program in Heliophysics

Data-driven space weather

What have we learned?

Data-driven space weather

What have we learned?

1. **Novel approach to space weather discovery: Network Analysis**

2. **Machine learning for space weather prediction**

Data-driven space weather

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2. **Machine learning for space weather prediction**

What have we learned?

GNSS signals are capable of being the backbone of the space weather observational system

- Coverage and cadence
- Critical ionospheric information
- Large volumes of data

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Success of ML methods requires:

1. A large volume of high-quality data
2. Explicit and well-defined task

What have we learned?

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1. A large volume of high-quality data
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➡ Data wrangling a significant obstacle